MODIS Enhanced Land Cover and Land Cover Change Product
Algorithm Theoretical Basis Documents (ATBD)

Version 2.0

MODIS Enhanced Land Cover and Land Cover Change
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1. Introduction

Three enhanced land cover and land cover change products are generated by the MODIS research team at University of Maryland (UMD). They are: the global 1km land cover classification at-launch product, the global 250m land cover change indicator product, and the global 500m global Vegetation Continuous Fields (VCF) product. The land cover indicator product is also called Vegetation Cover Conversion (VCC) product. Identifications of these products are listed in Table 1.1

Table 1.1 MODIS Land Cover and Land Cover Change Products by UMD

Product Name	Product Type	Product Number	Spatial Resolution	Temporal Resolution
Land Cover Classification Product	At-launch	N/A	1 km	Annual
Land Cover Change Indicator Product (VCC)	At-launch & Post-launch	MOD44A	250 m	Quarterly& annual
Vegetation Continuous Fields Product (VCF)	Post-launch	MOD44B	500 m	Annual

The global 1km land cover classification at-launch product is generated using NOAA's Advanced Very High Resolution Radiometer (AVHRR) data. It is created for other MODIS science team members to use as input of their MODIS products before a global land cover product based on MODIS data can be available.

The global land cover change indicator product at the 250m resolution is designed to provide early warning that land cover change is occurring. The limited spectral characteristics of the 250m bands will limit identification of the type of change that is occurring but the high spatial resolution should substantially improve the timeliness by which the existence of change is flagged compared with data at 1 km resolution.

The global vegetation continuous fields product is designed to overcome the arbitrariness of abrupt distinctions between land cover classes by representing land cover in each pixel with a proportion of basic cover components such as percentage woody tree cover or percentage herbaceous vegetation.

This document presents details about the input data, algorithms, and contents of these products. Considering the differences between these products in the aspects of input data, algorithm and product contents, this document is organized into three parts with each part describes one of the three products. Each of these three parts is further organized into four broad sections. Section 1 introduces the rationale of generating the product. Section 2 provides an overview and the technical background information. Section 3 presents the details of the algorithms employed in the generation of the product. Section 4 describes the constraints, limitations and assumptions of the product. This document represents a revision of the Section 5, "Additional Post-launch Products", of the MODIS land cover product (MOD12) ATBD Version 4.2, and is now named as Version 2.0 of UMD MODIS Enhanced Land Cover and Land Cover Change Products ATBD.

The following publications are related to the development of the above MODIS products and fully or partially supported by MODIS funding to the PI of the MODIS research team at University of Maryland:

1) M. Hansen, R. DeFries, J.R.G. Townshend, R. Sohlberg, 1999. Global Land Cover Classification at 1km Spatial Resolution Using a Classification Tree Approach. *International Journal of Remote Sensing. In press.*

2) M. Hansen and B. Reed. 1999. A Comparison of the IGBP DISCover and University of Maryland 1km Land Cover Classifications. *International Journal of Remote Sensing. In press.*

3) X. Zhan, R. DeFries, J.R.G. Townshend, C. DiMiceli, M. Hansen, C. Huang, R. Sohlberg. 1999. The 250m Global Land Cover Change Product from the Moderate Resolution Imaging Spectroradiometer of NASA's Earth Observing System. *Journal of Remote Sensing. In press.*

4) R. DeFries, M. Hansen, J.R.G. Townshend. 1999. Global Continuous Fields of Vegetation Characteristics: A Linear Mixture Model Applied to Multiyear 8km AVHRR Data. *Journal of Remote Sensing. In press.*

5) R. DeFries, J.R.G. Townshend, M. Hansen. 1999. Continuous Fields of Vegetation Characteristics at the Global Scale. *Journal of Geographic Research. In pres.*

2. The MODIS At-launch Product of Global Land Cover Classification at 1 km Resolution

2.1 Introduction

The generation of several MODIS products, such as the MODIS LAI and FPAR products, the MODIS Land Surface Temperature product and the MODIS/MISR BRDF/Albedo products, needs land cover classes data as their input. For this purpose , the MODIS science team has recommended two different versions of global 1km resolution land cover classification data product and called them as the two layers of the MODIS at-launch product of global 1km resolution land cover classification. These two layers are: the International Geosphere Biosphere Programme (IGBP) Data and Information System Land Cover product generated by Eros Data Center (EDC) and the global 1km land cover classification product generated by University of Maryland (UMD). This document describes the details of the UMD land cover product. Details of the EDC product are presented by Loveland et al. (1999). An inter-comparison of these two land cover product is provided in Section 2.4 of this document.

2.2 Overview and Technical Background

Vegetative land cover is an important variable in many earth system processes. Many general circulation and carbon exchange models require vegetative cover as a boundary layer necessary to run the model (Sellers et al. 1997). Vegetation also represents an important natural resource for humans and other species, and quantifying the types and extent of vegetation is important to resource management and issues regarding land cover change (Townshend 1992).

With increasing frequency, remotely sensed data sets have been used to classify global vegetative land cover. The primary goals in developing these products are to meet the needs of the modeling community and to attempt to better understand the role of human impacts on earth systems through land cover conversions. Recent work in classifying regional, continental and global land cover has seen the application of multi-temporal remotely sensed data sets, which describe vegetation dynamics by viewing their phenological variation throughout the course of a year (Verhoef et al. 1996). Tucker et al. (1985), Townshend et al. (1987) and Stone et al. (1990) have produced continental-scale classifications of land cover using this approach. For global land cover products, DeFries and Townshend have derived a one by one degree map (DeFries and Townshend 1994b) and more recently an 8km map using AVHRR data (DeFries et al. 1998). The current global land cover products are much finer in resolution than traditional climate modelers require, although there are some who have begun to take advantage of the added information which finer resolutions provide in the depiction of landscape heterogeneity (Dickinson 1995). As the resolutions of global data sets become finer, the ability to monitor short-term anthropogenically-induced land cover changes has increased. Sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) have resolutions sufficient enough to allow for global depictions of land cover change. Establishing a global baseline for land cover at 1km is an important step to understand how change can be depicted with newer sensors such as MODIS.

A 1 km resolution data set employing AVHRR data has been developed based on the recommendations from the International Geosphere Biosphere Programme (IGBP) for use in global change research (Townshend 1992). Loveland et al. (1999) have produced a 1km resolution global land cover layer, named the IGBP DISCover product, where each continent was classified separately and then stitched together. They used 12 monthly NDVI (Normalized Difference Vegetation Index) values in an unsupervised clustering algorithm that was supplemented with ancillary data analysis. The DISCover product has also been included as an at-launch land cover product for the MODIS sensor.

This document describes the development of the University of Maryland 1km data product to be included as another layer within the MODIS at-launch product. Building on the 8 km map and methodology of DeFries et al. (1998), this product provides an alternative 1km land cover data set based on the individual spectral bands as well as NDVI values. The approach involves a supervised method where the entire globe is classified using a classification tree algorithm. The tree predicts class memberships from metrics derived from the same AVHRR data employed by Loveland et al. (1999), except here all 5 spectral bands as well as NDVI are used. The application of the tree classifier utilizes an imposed hierarchy of vegetation form similar to that proposed and implemented by Running et al. (1994 and 1995), except that the relationships between multi-spectral data and vegetation type are empirically derived.

Maps produced using satellite data have advantages over traditional ground-based maps due to the continuous coverage and internal consistency of remotely sensed data sets. A primary reason for attempting to create maps from these data sets is the potential for creating more accurate products, where the areas of disagreement between products are less than past efforts compiled from ground-based maps (DeFries and Townshend 1994a). Classifying the entire globe at once allows for the consistent extrapolation of spectral signatures in order to improve the consistency of global land cover characterization. In the end, a limited amount of regional relabeling of pixels is required and reflects the limitations of the present method while pointing the way for improved iterations. In the absence of independent validation data, a comparison between the University of Maryland (UMd) land cover layer with other digital land cover maps is made later in this section, as well as with forest statistics produced by the United Nations Food and Agriculture Organization. These comparisons help identify potential strengths and weaknesses of the UMd product and also raise a number of issues which may help future efforts in creating improved products.

2.3 Algorithm Description

The MODIS at-launch land cover product is created using NOAA's Advanced Very High Resolution Radiometer (AVHRR) data when MODIS data are not available yet. This section describes the data used for creating the product first, then the classification algorithm is detailed. The third subsection presents the classification results followed by the product validation subsection. The fourth subsection compares the two existing MODIS at-launch products with each other.

2.3.1 Data

2.3.1.1 Training data

The majority of the training data were derived via the method described in DeFries et al. (1998), using an overlay of co-registered coarse resolution and interpreted high-resolution data sets. Previous work for the 1984 8km product consisted of interpreting 156 images, the great majority of which were Landsat Multispectral Scanner System (MSS) data sets. Interpretations were aided using ancillary data sets, a list of which is available, along with the 8km data plane at the following web site:

http://www.geog.umd.edu/landcover/global-cover.html.

After overlaying the 1km global data grid with the high-resolution data, only those 1km grid cells which were interpreted from the MSS as consisting of 100 percent of the cover type of interest were included in this training set. However, manipulating and analyzing the 1km data set at full resolution proved to be beyond the available computing resources, so a subset of the entire data set, including the training data, was then derived. Roughly every 5th pixel was sampled across each row and line of the data set in order to create a much-reduced, but viewable and usable subset of 7205 pixels by 3122 lines. From this subset, 27,031 pixels were taken from the high-resolution scenes as training sites.

Additional MSS scenes outside of the 156 original images were needed to address some shortcomings seen in the 8km land cover product. The original scenes were selected from areas where three largely ground-based global land cover characterizations agreed (Matthews 1983; Olson et al. 1983; Wilson and Henderson-Sellers 1985). For some classes, this greatly limited the successful depiction of land cover across all latitudes. For example, the wooded grassland class, better described by its definition of 10-40 percent tall woody canopy cover, had training sites only within the tropical regions of the globe. Thus, the depiction of areas with 10-40 percent tall woody canopy within temperate and boreal zones was limited. Clearly, there are large areas outside of the tropics which have land cover fitting the description of this class. To address this issue and others like it, MSS thumbnail images were downloaded using the Global Land Information System (GLIS) from the EROS Data Center (http://edcwww.cr.usgs.gov/webglis/) and physical features were identified using the same ancillary data as was used to create the original training sites. This procedure added 10,218 pixels to the database, yielding a total of 37,249 training pixels.

The entire exercise of augmenting the training data was based on interpretative analysis of the 8km product as well as some preliminary work with 1km data. The goal of adding to the training sites was to improve upon the limitations of the 8km map. No quantitative sampling procedure was available in order to guide the acquisition of the training data, as no reliable *a priori* knowledge of their global distributions exists.

2.3.1.2 AVHRR Data

The data used in this classification come from the Advanced Very High Resolution Radiometer (AVHRR) 1km data set processed at the EROS Data Center under the guidance of the International Geosphere Biosphere Programme (Eidenshink and Faudeen 1994; Townshend et al. 1994). For this project, data are radiometrically calibrated, geo-registered to the 1km Goode's Interrupted Homolosine equal area projection, composited over a ten-day period using maximum Normalized Difference Vegetation Index (NDVI), and then atmospherically corrected for ozone and Rayleigh scattering and solar zenith angle to yield surface reflectances. From a set of 12 data layers, the following were included in this study: channel 1 (visible red reflectance, 0.58-0.68 microns), channel 2 (near infrared reflectance, 0.725-1.1 microns), channel 3 (thermal infrared, 3.55-3.93 microns), channel 4 (thermal, 10.3-11.3 microns), channel 5 (thermal, 11.5-12.5 microns) and the NDVI (channel 2- channel 1)/(channel 2 + channel 1). The first twelve months produced for this data set were used in this classification beginning April 1, 1992 and ending March 31, 1993.

To reduce data volumes and cloud contamination, a maximum NDVI composite was created for every month, along with all 5 associated channel values. This, however, did not remove all noise from the data set, and a filtering of the data was performed in the context of a time series by identifying and removing data spikes (DeFries et al. 1998). Since there is no quality control flag for the 1km data, each monthly value of each band was viewed in isolation and compared to the standard deviation of the remaining monthly values. Those monthly values which were greater than seven standard deviations away from the mean of the remaining eleven months were removed. The value of seven standard deviations was chosen through visual inspection of the data and found to be a conservative level which removed the most obvious spikes. The metrics calculated from the AVHRR time series are very sensitive to noisy data, including maximum and minimum annual metrics (see section 3.3), and the removal of inordinately extreme values preserves their utility. Other AVHRR processing techniques note the presence of digital counts of extreme low and high values which are not readily detectable, even in a data set production mode (Agbu and James 1994). The attempt here was to find a simple remedy which reduced the problem of noise without removing useful data.

Preliminary work on the 1km data revealed a number of characteristics which dictated some modifications to the classification methodology used for the 8km product. In general, the 1km data set appears to have more artifacts and cloud contamination than the 8km Pathfinder data set. The 8km data set is derived from Global Area Coverage (GAC) 4km data (James and Kalluri, 1994), which is continuously recorded on board the NOAA platforms, while the 1km data set uses Local Area Coverage (LAC) 1km data, which must be recorded by regional receiving stations. The result for the 1km data set is a less continuous product temporally, as receiving stations are not always operating. This yields a more cloud contaminated composite. Also, the geo-referencing for the 8km uses on-board navigation to bin pixels, while the 1km uses ground control points. For any data scan at 1km, the swath was divided into areas corresponding to the sections in the Goode projection. Any section not having a minimum number of ground control points was excluded, unlike the 8km product, which retained all data. This also results in a less clean composite as the number of samples entered into the compositing scheme is substantially reduced. Both compositing schemes used maximum NDVI, and then applied an atmospheric correction. Binning on NDVI results in composites being biased in the forward scatter direction due to bidirectional reflectance distribution function (BRDF) effects (Cihlar et al. 1994; Holben 1986), resulting in less clean time series, particularly for channels 1 and 2. This also increases the presence of pixels with distorted view geometries. Misplaced scans are also present due to poor header information on the input data (Eidenshink, pers. comm.). While both the 8km and 1km data sets have many common problems, such as no BRDF correction, the aforementioned differences can have a significant effect on the production of like products, and lead to a need for somewhat different treatments of the data in producing land cover maps.

2.3.2 Classification scheme

2.3.2.1 Algorithm

A decision tree was used to classify the dependent variable of class membership using the independent variables of AVHRR metrics. Decision tree theory (Breiman et al. 1984; Quinlan 1993; Venables and Ripley 1994) has previously been used to classify remotely sensed data sets (DeFries et al. 1998; Freidl and Brodley 1997; Hansen et al. 1996), and offers some advantages over other classification methods. Trees are a non-parametric, hierarchical classifier which predicts class membership by recursively partitioning a data set into more homogeneous subsets. This procedure is followed until a perfect tree (one in which every pixel is discriminated from pixels of other classes, if possible) is created with all pure terminal nodes or until preset conditions are met for terminating the tree's growth. The method used here is that of the Splus statistical package (Clark and Pergibon 1992), which employs a deviance measure to split data into nodes which are more homogeneous with respect to class membership than the parent node. The reduction in deviance, (*D*) is calculated as:

$$D = D_s - D_t - D_u \qquad (2.1)$$

where *s* is the parent node, and *t* and *u* are the splits from *s*. Right and left splits along the digital counts for all metrics are examined. When *D* is maximized, the best split has been found, and the data are divided at that digital count and the process repeated on the two new nodes of the tree. The deviance for nodes is calculated from the following:

$$D_i = -2\Sigma n_{ik} \log p_{ik} \qquad (2.2)$$

where n_{ik} is the number of pixels in class k in node i and p is the probability distribution of class k in node i.

Trees usually overfit the training data and a pruning procedure is needed to better generalize the relationships between the dependent and independent variables. In other words, the tree can fit the training data too well by growing on noise and errors. To avoid this, a pruning procedure is employed to better generalize the predictive ability of the tree. Pruning is performed by splitting the data into two sets and using one to grow the tree and another to prune it by eliminating nodes which increase errors within the pruning data set. In this study, pruning was performed by visual interpretation due to problems inherent in both the training and the AVHRR data, as will be discussed shortly.

Because trees are non-parametric and non-linear, multiple terminal nodes are created for classes which have multi-modal distributions in spectral space. This allows for the clearer depiction of the intraclass variability which exists at the global scale. Trees are also useful for identifying classes which represent subsets of a continuous parameter, such as tree canopy for wooded grasslands, woodlands and forests. Trees operate not on statistics of central tendency, but along the thresholds in multi-spectral space which best characterize boundaries between classes. Hansen et al. (1996) found that a single classification tree threshold was superior to a maximum likelihood classifier in identify tall from short global vegetation. However, since the training pixel counts are used to estimate probabilities, larger classes can be overemphasized in optimizing the splits and in the assignments of terminal nodes. Smaller classes are easily identified within trees if they are dominant in any part of the multi-spectral space. But, if smaller classes are mixed with larger classes, the smaller class can be lost via the assignment of terminal nodes to the classes with a dominant proportional representation.

The hierarchical nature of trees yields explicit relationships between the dependent variable, class membership, and the independent variables of multi-temporal metrics. In so doing, it allows for a readier biophysical interpretation through the description of vegetation characteristics such as height of vegetation and canopy closure. This ease of interpretation is unique among popular remote sensing classifiers and allows for the input of an expert analyst in correcting splits associated with faulty or contradictory training data.

Table 2.1 Comparison of University of Maryland class definitions to the IGBP-DIS definitions.

University of Maryland vegetation classes

Cover types in common with IGBP

Evergreen Needleleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 5 meters. Almost all trees remain green all year. Canopy is never without green foliage.

Evergreen Broadleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 5 meters. Almost all trees remain green all year. Canopy is never without green foliage.

Deciduous Needleleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 5 meters. Trees shed their leaves simultaneously in response to cold seasons.

Deciduous Broadleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 5 meters. Trees shed their leaves simultaneously in response to dry or cold seasons.

Mixed Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 5 meters. Consists of tree communities with interspersed mixtures or mosaics of needleleaf and broadleaf forest types. Neither type has <25% or >75% landscape coverage.

Woodlands: Lands with herbaceous or woody understories and tree canopy cover of >40% and <60%. Trees exceed 5 meters in height and can be either evergreen or deciduous.

Wooded Grasslands/Shrublands: Lands with herbaceous or woody understories and tree canopy cover of >10% and <40%. Trees exceed 5 meters in height can be either evergreen or deciduous.

Closed Bushlands or Shrublands: Lands dominated by bushes or shrubs. Bush and shrub percent canopy cover is >40%. Bushes do not exceed 5 meters in height. Shrubs or bushes can be either evergreen or deciduous. Tree canopy cover is <10%. The remaining cover is either barren or herbaceous.

Open Shrublands: Lands dominated by shrubs. Shrub percent canopy cover is >10% and <40%. Shrubs do not exceed 2 meters in height can be either evergreen or deciduous. The remaining cover is either barren or of annual herbaceous type.

Grasslands: Lands with continuous herbaceous cover and <10% tree or shrub canopy cover.

Croplands: Lands with >80% of the landscape covered in crop-producing fields. Note that perennial woody crops will be classified as the appropriate forest or shrubs land cover type.

Barren: Lands of exposed soil, sand, rocks, snow or ice which never have more than 10% vegetated cover during any time of the year.

Urban and Built-up: Land covered by buildings and other man-made structures. Note that this class will not be mapped from the AVHRR imagery but will be developed from the populated places layer that is part of the Digital Chart of the World (Danko, 1992).

Water Bodies: Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt water.

IGBP-DIS Land Cover Working Group vegetation classes

Cover types in common with UMd

Evergreen Needleleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.

Evergreen Broadleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.

Deciduous Needleleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 2 meters. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.

Deciduous Broadleaf Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 2 meters. Consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.

Mixed Forests: Lands dominated by trees with a percent canopy cover >60% and height exceeding 2 meters. Consists of tree communities with interspersed mixtures or mosaics of the other four forest cover types. None of the forest types exceeds 60% of the landscape.

Woody Savannas: Lands with herbaceous and other understory systems, and with forest canopy between 30-60%. The forest cover height exceeds 2 meters.

Savannas: Lands with herbaceous and other understory systems, and with forest canopy between 10-30%. The forest cover height exceeds 2 meters.

Closed Shrublands: Lands with woody vegetation less than 2 meters tall and with shrub canopy cover >60%. The shrub foliage can be either evergreen or deciduous.

Open shrublands: Lands with woody vegetation less than 2 meters tall and with shrub canopy cover between 10-60%. The shrub foliage can be either evergreen or deciduous.

Grasslands: Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.

Croplands: Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrubs land cover type.

Barren: Lands of exposed soil, sand, rocks or snow and never has more than 10% vegetated cover during any time of the year.

Urban and Built-up: Land covered by buildings and other man-made structures. Note that this class will not be mapped from the AVHRR imagery but will be developed from the populated places layer that is part of the Digital Chart of the World (Danko, 1992).

Water Bodies: Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt water.

Permanent Wetlands: Lands with a permanent mixture of water and herbaceous or woody vegetation that cover extensive areas. The vegetation can be present in either salt, brackish, or fresh water.

Cropland/Natural Vegetation Mosaics: Lands with a mosaic of croplands, forest, shrublands, and grasslands in which no one component comprises more than 60% of the landscape.

Snow and Ice: Lands under snow and/or ice cover throughout the year.

Covers not in common with UMd.

Table 2.2 Metrics employed in the production of the University of Maryland 1km product using AVHRR data from April 1992 to March 1993

1) maximum NDVI value
2) minimum NDVI value of 8 greenest months
3) mean NDVI value of 8 greenest months
4) amplitude of NDVI over 8 greenest months
5) mean NDVI value of 4 warmest months
6) NDVI value of warmest month
7) maximum channel 1 value of 8 greenest months
8) minimum channel 1 value of 8 greenest months
9) mean channel 1 value of 8 greenest months
10) amplitude of channel 1 over 8 greenest months
11) channel 1 value from month of maximum NDVI
12) mean channel 1 value of 4 warmest months
13) channel 1 value of warmest month
14) maximum channel 2 value of 8 greenest months
15) minimum channel 2 value of 8 greenest months
16) mean channel 2 value of 8 greenest months
17) amplitude of channel 2 over 8 greenest months
18) channel 2 value from month of maximum NDVI
19) mean channel 2 value of 4 warmest months
20) channel 2 value of warmest month
21) maximum channel 3 value of 8 greenest months
22) minimum channel 3 value of 8 greenest months
23) mean channel 3 value of 8 greenest months
24) amplitude of channel 3 over 8 greenest months
25) channel 3 value from month of maximum NDVI
26) mean channel 3 value of 4 warmest months
27) channel 3 value of warmest month
28) maximum channel 4 value of 8 greenest months
29) minimum channel 4 value of 8 greenest months
30) mean channel 4 value of 8 greenest months
31) amplitude of channel 4 over 8 greenest months
32) channel 4 value from month of maximum NDVI
33) mean channel 4 value of 4 warmest months
34) channel 4 value of warmest month
35) maximum channel 5 value of 8 greenest months
36) minimum channel 5 value of 8 greenest months
37) mean channel 5 value of 8 greenest months
38) amplitude of channel 5 over 8 greenest months
39) channel 5 value from month of maximum NDVI
40) mean channel 5 value of 4 warmest months
41) channel 5 value of warmest month

2.3.2.2 Classes

The IGBP has developed a list of classes for use within global change research and to which the 1km MODIS at-launch product and post-launch products will conform (Rasool 1992). The UMd class definitions closely fit this scheme and are listed along with corresponding IGBP classes in Table 2.1. The 1km training areas are derived from 156 high-resolution scenes. These were originally interpreted for the 8km map which employed a classification scheme for use with the Simple Biosphere (SiB) general circulation model (Sellers 1997). The SiB scheme does not have agricultural mosaic, wetlands or snow and ice classes. As a result, the mosaic and wetlands classes are absent from this classification, while the IGBP snow and ice cover class is included in the bare ground class. The urban and built-up class was taken directly from the EDC 1km IGBP classification by Loveland (1999), which was in turn obtained from the Digital Chart of the World (Danko 1992). The water layer was taken from a preliminary water mask made for the MODIS sensor in a sinusiodal projection and reprojected into the Interrupted Goode Homolosine projection for use with this project. The SiB mosses and lichens class does not exist within the IGBP scheme, and scenes from this class were reinterpreted to extract other covers where possible. More subtle differences between the UMd and the IGBP schemes, such as height of trees, are irreconcilable and differ largely because of the definitions used by the ancillary sources in interpreting the high-resolution data.

2.3.2.3 AVHRR metrics

A set of 41 metrics was created for input into the decision tree. The first 29 metrics were created from values associated with the 8 greenest months of the year. These metrics differ from the ones used to derive the 8km map. The 8km metrics used all 12 months of 1984 Pathfinder 8km data in the classification, and this produced a number of nodes associated with snow cover. Snow cover, especially relating to the distribution and number of training pixels within and without the snow area, can produce undesired results. By binning all metrics on only the 8 greenest months, snow effects are largely limited to those places with perpetual snow and ice cover and very high-latitudes, while still retaining most of the seasonal variability associated with vegetation phenology. The 8 greenest months are not necessarily consecutive, but represent the 8 months with the clearest view of green vegetation. In this manner, globally applicable, timing insensitive metrics with minimized cloud presence are created. The metrics used included maximum, minimum, mean and amplitudes for all bands associated with the eight greenest months. Individual band values associated with peak greenness were also derived.

Using only 8 months of data means that for areas like the tropics and much of the temperate zone, 4 months of useful data were thrown away. To try and recapture some of this information, metrics were binned on the 4 warmest months, as measured by channel 4, and two additional metrics per band and for NDVI were calculated. These were means associated with the four warmest months and individual values occurring at maximum channel 4 temperature. The four warmest months were found to be associated with the dry season, or senescent phase of much tropical vegetation. By compositing on these values, data not used in the 8 greenest months can be included for some areas without introducing snow values at high latitudes and elevations. The metrics derived from the 1992-93 year for bands 1-5 and NDVI are listed in Table 2.2.

2.3.2.4 Procedure

The classification procedure followed that of the 8km product except for the use of a cascading two-class hierarchy of trees in implementing the classification tree algorithm. An initial attempt at using the previous methodology revealed the inability to create a single simplified tree such as the 8km tree which described the globe in 57 nodes. One potential reason is the increased heterogeneity of the Earth's surface at 1km which precludes the creation of a single, simple global tree. Secondly, the 1km data is more cloud contaminated than the 8km data set, as mentioned previously, due to different recording procedures, geo-registering and compositing techniques. This results in a more complex tree structure than the one derived for the relatively cleaner 8km data. Thus, the decision was taken to create an imposed tree hierarchy, shown in Figure 2.1, somewhat similar to the one used by Running et al. (1995). In this manner, only two classes are depicted within any single tree, allowing for a simplified, structured approach and easier interpretation of the results. The original training pixels were run through the successive trees and a preliminary result was obtained. Pruning based on visual interpretation of this preliminary global map was then applied where nodes were accepted or rejected based on their global geographic distributions. From this, a subset of pixels associated with approved nodes was created. These pixels were then rerun through the tree structure and a final tree was derived. These trees were again pruned based on visual interpretation to produce the final map.

For the both the UMd 1km and 8km maps, an automated classification algorithm is employed to depict land cover, but obvious errors in the product make it necessary to apply an interpretive step. Figure 2.2 outlines the steps in the procedure along with some of the sources of error within this product which mandate that an interpretative pruning be applied. Cloud contamination, bad scan lines, missing data, geometric misregistration, and incorrect ancillary data can lead to the production of anomalous nodes which cannot be eliminated except by a subjective step. For this study, pruning was performed through manually clipping nodes, relabeling nodes, and finding alternative splits for nodes which yielded depictions of land cover not consistent with known global distributions. Although the derivation of the trees cannot be duplicated, the application of these trees will result in the same map product. In this sense, the procedure is reproducible given the metrics and the trees, but the product reproduced represents a mix of objectively and subjectively derived relationships. Efforts are underway to improve the ability to derive land cover products more objectively by applying more sophisticated algorithms for growing and pruning trees (Quinlan 1993). Upon application of the final trees, a regional relabeling is performed on pixels which do not agree with known global geographic distributions.

2.3.3 Results

After the initial run of the training data through the tree hierarchy and pruning procedure, a subset of 26,208 pixels was taken to create the final classification tree structure. All trees were created using the 7205 by 3122 pixel subset of the 1km data. The final trees were then run on the entire 1km data set. No sieve was applied.

Among the most frequently used metrics for all trees were minimum annual red reflectance and maximum annual NDVI. Figure 2.3 shows subsets of boreal, temperate and tropical areas for these metrics with the same spectral enhancements. These subset windows will be used to illustrate certain qualities of the product as the discussion of the tree hierarchy is developed.

2.3.3.1 Hierarchical classification tree

2.3.3.1.1 Vegetated/bare ground tree

The first tree was a vegetated/non-vegetated tree used to classify bare ground (Figure 2.4). For all trees depicted, only the dominant nodes accounting for over 5% of the respective class' land areas are shown. A simple maximum annual NDVI threshold provides greatest initial discrimination for the vegetated/non-vegetated tree. In Figure 2.5a, the land areas associated with the dominant nodes for the tree are highlighted. Areas such as volcanic features in the Sahara Desert are not easily discriminated with a single split (shown in black as lesser nodes), and extra nodes were required that largely accounted for these barren ground subtypes. Barren areas with a maximum NDVI greater than 0.155 are associated with a misplaced AVHRR 1km data set swath in the Atacama desert. The rest of the black area is associated with places having a peak NDVI less than 0.155. Outcrops in the Sahara and other places are confused with sparse grasslands in China, and additional splits are needed to depict them. Volcanic outcrops of the

Sahara have been analyzed before in efforts to account for background soil reflectances which make certain areas spectrally similar to sparsely vegetated ones (Huete and Tucker, 1991). The results here reflect the difficulty in separating these areas using NDVI alone, and different spectral information through the use of additional splits is needed to characterize them.

2.3.3.1.2 Tall/short vegetation tree

This tree was meant to separate woodlands and forests with nearly closed tall canopies from open parklands, shrublands, croplands and herbaceous covers. Figure 2.6 shows the tree's structure and Figure 2.5b where the dominant nodes map globally. In general, low minimum annual visible red values (<5.3% reflectance) successfully discriminated woodlands and forests. Exceptions to this relationship included non-woody areas with water present, such as inundated grasslands, areas of rice production and other wetland formations. Commission errors of woody classes are associated with some non-woody areas for these types of land cover. Many tropical inundated grasslands were confused with needleleaf evergreen stands in the visible and near-infrared, and temperature values were used to separate the two. This, however, did not resolve the characterization of similar wetlands at higher latitudes.

Some croplands, particularly in the midwest of the United States, also had very dark minimum red values and created confusion between croplands and woodlands. Part of this problem may be due to bad data in the 1km data set. For example, Figure 2.3b shows the minimum annual channel 1 metric for the Midwest USA. The line in the image is the Mollweide/Sinusoidal boundary of the Goode projection. The dark northern portion creates a node in the woody/non-woody tree specific to itself, indicating a possible problem with the data set. Figure 2.5b shows this area in black as one of the lesser nodes not easily discriminated along with the rest of the woody and non-woody types. This type of problem is hard to isolate in a global approach and can create undesirable results.

In general, along forest/non-forest boundaries it is apparent that the extent of forest stands is exaggerated. For example, clearings of grasslands within the Amazon basin are reduced in size as if a buffer of forest were added to the boundary. This is the result of binning on maximum NDVI, retaining data from low scan angles and georegistration inaccuracies. When combining these effects, the greener class along any class boundary usually is overemphasized. This loss of heterogeneity and bias of dominant classes has been discussed by others (Moody and Woodcock 1994; Cushnie 1987) and users should be aware of this problem.

One noticeable area lacking in woodlands in this product is West Africa. While woodlands are mapped, they are not present in this product as much as ancillary data indicate they should be

http://www.geog.umd.edu/landcover/global-cover/global-resources.html

Figure 2.3c shows a two band composite of an area in West Africa. In general, West African woodlands are considerably brighter than other woody areas, such as the miombo woodlands of Southern Africa, or the Gran Chaco of Argentina, possibly reflecting a longer history of anthropogenic disturbance in the region. Low minimum annual red reflectance for tall woody areas represents the combined effects of canopy shadowing and chlorophyll absorption. For most of West Africa, high minimum annual red reflectance values limit the areal extent of forests and woodlands. Figure 2.3c also shows the problem of persistent cloud cover along the coast of West Africa in affecting the minimum channel 1 metric. The classification of grasslands along the western coast of the image is suspected of being largely the cause of cloud presence in all monthly composites. This area, according to ancillary information, has considerably more forested land.

It is of interest that the first woody/non-woody split of minimum annual red reflectance was nearly the same as that derived for our 8km land cover classification using 1984 Pathfinder data, 5.35 percent compared to 5.38 percent. The potential reproducibility of tree splits between data sets and over time has implications for not only land cover mapping, but also change detection. A reproducible tree structure over time would allow for the depiction of spectral migration and change.

2.3.3.1.3 Forest/woodland tree

Woodlands were also distinguished from forests based on minimum visible red values. Figure 2.7 shows the forest/woodland tree while Figure 2.5c shows the spatial extent of the dominant nodes. Some tropical woodlands were as dark and green as tropical forests and temperature bands, such as the mean of the four channel 5 values associated with the warmest 4 months of the year, were used to stratify these areas. This metric helped create a fairly clear forest/woodland boundary in Central Africa, but may have increased confusion between some more seasonal tropical forests and adjacent woodlands. Ancillary data from Asia referring to deciduous forests and African sources for miombo woodlands are not reconciled in the metrics used here and errors between tropical seasonal forest and woodlands are suspected to exist in areas such as Asia and West Africa. The depiction of woodlands revealed the heterogeneity of areas such as the boreal forest, and within fragmented forest/agricultural mosaics such as the southeastern United States. The global approach of applying a set of universal splits revealed a lack of true forest in a number of areas such as the Atlas Mountains and the hills of east-central India in contradiction to ancillary sources which depict extensive forest stands.

2.3.3.1.4 Remaining trees

Descriptions of the remaining trees can be found in the metadata of the 1km product at the aforementioned website. Important aspects include:

- Mixed/pure leaf type forest tree
  - mixed forests defined within 45-60 degrees latitude are separated largely by the mean channel 4 of the 8 greenest months metric and maximum NDVI
  - maximum NDVI is repeatedly used
  - many high-latitude broadleaf forests are classified as mixed forest due to lower maximum NDVI values
  - broadleaf forests mixed with non-forest covers are often labeled mixed forest, creating a buffering affect around core broadleaf areas (see Figure 2.3a)
- Broadleaf/needleleaf forest tree
  - minimum channel 3 separates tropical broadleaf from extratropical needleleaf forest
  - maximum NDVI separates temperate broadleaf from needleleaf forest
  - lush evergreen needleleaf areas, such as that found in the Pacific Northwest, and Araucaria forests in South America, are confused with broadleaf evergreen forest
  - Eucalyptus forests in Australia and elsewhere map as needleleaf evergreen forests
- Needleleaf evergreen/deciduous forest tree
  - amplitude of NDVI largely separates these leaf types
  - needleleaf deciduous forests confused with mixed forests
- Broadleaf evergreen/deciduous forest tree
  - minimum channel 3 separates temperate from tropical broadleaf forests
  - mean of the four channel 5 values associated with the four warmest months separates tropical deciduous from tropical broadleaf forests
  - amplitude of NDVI separates temperate deciduous forests from other evergreen forests not separated by the channel 3 split
- Sparse trees (wooded grassland)/croplands, grass or shrubs tree
  - high intraclass spectral variability, largest wooded grassland node accounts for only 17 percent of class total
  - minimum red reflectance, infrared reflectance at peak greenness and minimum channel 3 are the metrics of the first three splits

    - most difficult class to map since it represents wide range of partial woody covers, for example: scrub savannas, boreal transitional woodlands, and crop/forest mosaics
- Croplands/shrubs and grass tree
    - NDVI and near-infrared metrics are first two used in this tree
    - mechanized agriculture is in general agreement with ancillary data
    - agriculture in developing nations poorly depicted, as is all low biomass agriculture, due to the difficulty in separating cropping from natural background phenologies and errors of omission and commission exist for many areas
- Grass/shrubs tree
    - mean red reflectance and channel 5 and NDVI means for the warmest four months are used in the first three splits
    - pastures within temperate cropping areas are not depicted
    - semi-arid and very high-latitude grasslands not well depicted
- Open/closed shrubs tree
    - temperature and NDVI metrics separate shrub classes
    - confusion between these two classes and grasslands suspected to exist as background soil reflectances make discrimination difficult (Huete and Tucker 1991)

2.3.3.2 Regional relabeling

The last step was a regionally-based reassignment of obvious inaccuracies which were performed to remove clearly erroneous results. This modification of the product changed only 0.67 percent of the total land area, and represents areas spectrally inseparable within the present training data signatures. The following is a summary of classes which were remapped for this purpose: above boreal zone agriculture mapped to grassland, exterior to Siberia deciduous needleleaf forest mapped to mixed forest, needleleaf evergreen forest in Australia mapped to broadleaf evergreen forest, needleleaf forest in humid tropical basins such as the Amazon and the Congo mapped to woodland, shrub classes on volcanic outcrops in the Sahara mapped to bare ground, evergreen broadleaf forest in temperate latitudes mapped to evergreen needleleaf forest, extensive agriculture on the Tibetan plateau mapped to grassland, broadleaf evergreen forest in the miombo belt of southern Africa mapped to woodland and two reassignments of classes due to misplaced AVHRR swaths. Table 2.3 shows the number of pixels per class changed in this manner. Needleleaf deciduous forest is by far the most affected. Most of the pixels changed for this class represent mixed forest pixels. One possible explanation for the inability of this approach to cleanly delineate needleleaf deciduous forest may be the possible presence of broadleaf forest within the needleleaf deciduous training sites. When viewing maximum NDVI values for the deciduous versus evergreen needleleaf forests, deciduous forest has a median value of .64 compared with an evergreen value of .61. Higher peak greenness may be an indicator of the presence of broadleaf types within this class.

Table 2.3 Re-mapping of likely misclassifications based on application of regional rules. Shown are re-mapped area and remapped area as a percent of total class area as predicted by the classification tree.

Class	Remapped area in sq. km	% remapped/ class total
Needleleaf evergreen forest	309747	5.54
Broadleaf evergreen forest	121271	1.08
Needleleaf deciduous forest	174047	23.41
Broadleaf deciduous forest	51238	2.84
Mixed forest	53988	1.62
Woodland	27240	0.16
Wooded grasslands	31993	0.14
Closed shrublands	0	0.00
Open shrublands	37400	0.21
Grassland	224	0.00
Cropland	150404	1.33
Bare ground	11747	0.04
Urban and built-up	0	0.00
Global totals	969299	0.67

2.3.3.3 Final global land cover classification

The areal extent of each class is shown in Table 2.4 and the final product in Figure 2.8. The comparison of these totals to the 1984 8km product can be seen in Figure 2.9. Note the marked increase in wooded grassland in the 1km product and a corresponding decrease in more forests and woodlands. Beyond the addition of more intermediately woody training sites, the nature of the resampling in producing the GAC and 8km Pathfinder data would also make an 8km product more forested. The resampling of GAC data has been studied and shown to be biased towards the greenest covers and reducing spatial heterogeneity (Justice et al. 1989). This would tend to smooth mosaic areas and reduce the expression of intermediate woody covers. The most greatly reduced forest in terms of area is the needleleaf evergreen class. This is the result of the addition of more open canopy needleleaf training areas delineated in order to reduce the dominance of this class in certain regions of the 8km product. The shrub classes appear to disagree because the 8km product includes a class for mosses and lichens (tundra), and this area is mapped mostly as shrublands in the 1km map.

Table 2.4 Total class areas for the University of Maryland 1 km product

Class	Area in sq. km	%
Needleleaf evergreen forest	5277925	3.67
Broadleaf evergreen forest	11138639	7.74
Needleleaf deciduous forest	569299	0.40
Broadleaf deciduous forest	1752105	1.22
Mixed forest	3272545	2.28
Woodland	16533042	11.50
Wooded grasslands	22653618	15.75
Closed shrublands	7436875	5.17
Open shrublands	17938741	12.47
Grassland	12382238	6.61
Cropland	11126625	7.74
Bare ground	33583362	23.28
Urban and built-up	260092	0.18
Total	143825106	100.00

2.3.3.4 Reproduction of training data

All of the training data were used in the production of the trees. Since no independent data yet exist for validating global data sets, it is useful to examine the results of the product compared to the training pixels. The majority of the confusion within the training data relates to physiognomically similar class types and classes representing mixed assemblages. There is relatively little confusion between core classes representing dominant vegetation forms and forest types. For example, the training agreement when viewing the confusion between only the classes of evergreen needleleaf and broadleaf forests, deciduous needleleaf and broadleaf forests, shrubland, grassland, cropland and bare ground is 88 percent (positively identified pixels of these classes/(positively identified pixels of these classes + errors only across these classes)). By adding the mixed forest class, woodlands, wooded grasslands, and open and closed shrublands, significant additional confusion results. The total training accuracy for all classes is reduced to 69 percent (total positively identified pixels for all classes/total number of training pixels). The accuracies for all classes are shown in Figure 2.10. The best training accuracies are for the most homogeneous cover types such as bare ground (99 percent = positively identified bare ground pixels/total number of bare ground training pixels), open shrubs (84 percent) and broadleaf evergreen forest (80 percent). However, nearly one-third (32 percent) of mislabeled pixels are errors of commission or omission for the woodland class. Over one-half (55 percent) of training errors are associated with either woodland or wooded grassland pixels. Only one-third (33 percent) of all errors represent confusion between the aforementioned core classes.

The mixed class types are particularly problematic due to the reliance on ancillary data sets in delineating training sites. An example of forest/woodland confusion can be taken from a set of pixels interpreted from an MSS scene covering part of eastern India. All of the pixels from the Chota Nagpur Plateau area were characterized as broadleaf deciduous forest but were classified as woodland in the final product due to the fact that within the metrics they are spectrally most similar to other woodland training sites. The original interpretation of the MSS scene was based on ancillary map data depicting the area as forest, but pixels from this scene have a mean minimum annual red reflectance of 5.1% compared to 3.8% for other global forest training pixels. Thus, within the tree structures, these pixels were labeled as woodland and not forest. A single misclassified scene such as this one can greatly reduce training accuracies. The pixels from this Indian scene represent 17% of all deciduous broadleaf forest training pixels and are counted as training errors.

The training accuracy numbers are less than that achieved in our 8km effort, which had an overall training accuracy, for a set-aside data set, of 81 percent. This reflects the increased heterogeneity of the earth surface at 1km, the greater presence of noise and other data problems within the 1km data set, and a proportional increase of mixed classes within the 1km training pixels.

2.3.4 Validation

A global validation data set does not exist with which to measure the accuracy of this land cover product, although an effort is underway to develop such a database at 1km resolution (Belward 1996). Many researchers have stressed the need for statistically rigorous validation efforts for maps being used for scientific investigations and policy decisions (Stehman and Czaplewski 1998). However, the validation of this 1km data product is beyond available resources at this time. In order to evaluate this map, a few comparisons were made with other existing regional data sets which employed high-resolution data sources. Although these cannot be used as validation data, they do help characterize the map by yielding a measure of concurrency between products which were derived entirely independently from one another.

2.3.4.1 Environmental Protection Agency Region 3 Characterization

The United States Environmental Protection Agency has begun an effort to classify the 10 Federal Standard Regions as part of an effort called the Multi-Resolution Land Characteristics Consortium National Land Cover Data Base (MRLC) (Vogelman et al. 1998). To date only region three, consisting of Delaware, the District of Columbia, Maryland, Pennsylvania, Virginia and West Virginia, has been finished. It is a 30 meter map product derived from Landsat Thematic Mapper data and characterizes some classes in common with the UMd product. By reprojecting and resampling the classes to their proportional representation at 1km, an evaluation of the agreement between the two can be undertaken.

Much of this area is taken up by the Appalachian chain of mountains, which are largely forested, while the valley bottoms and the eastern coastal plain consist of a mosaic of remnant forests and agriculture. By taking the most frequently occurring land cover at the 30 meter spatial resolution within geo-registered 1km squares, a map of the EPA's product aggregated to 1km was produced. Both land cover products, as aggregated to the UMd scheme, are shown in Figure 2.11a and 2.11b. This area is dominated by broadleaf deciduous forest, and many valleys present at fine resolutions are not captured at 1km resolution. The overall agreement per pixel is 65 percent. When examining homogeneous, or core area, 1km pixels which consist of greater than 90 percent one cover type within the high-resolution map layer, the agreement increases to 81 percent. The corresponding forest/non-forest numbers are 83 percent and 92 percent. In all comparisons, forest includes all 5 forest types and non-forest includes the remaining 8 classes.

The percent agreement numbers should not be confused with accuracies, but are reported only in order to aid in the visual interpretation of the graphics and to reflect a measure of general thematic agreement. Although viewing core areas can yield overly optimistic results (Hammond and Verbyla 1996), it is worth examining here for a number of reasons. First, some mosaiced areas for the MRLC data do not have a single cover which is dominant at 1km. For EPA Region 3, these areas are most likely to be represented in the 1km map as a partial tree cover class such as woodlands or wooded grassland. These intermediate classes were not included in the MRLC classification scheme and a straightforward comparison cannot be made. Also, AVHRR data reduces the heterogeneity present in mosaiced areas while this spatial complexity remains even in the resampled MRLC data. Evaluating core areas yields a measure of thematic agreement while minimizing problems associated with this inherent incompatability.

Grasslands in the MRLC map are confused with croplands and wooded grassland in the UMd map. Pastures occurring within intensive agricultural areas were not trained on for the 1km data set and this could lead to errors of omission for the grassland class. Areal comparisons of all regional data sets with the UMd map are shown in Figure 2.12.

2.3.4.2 European Coordination of Information on the Environment data

Digital maps for much of western Europe are now available in the European Coordination of Information on the Environment (CORINE) data set produced by the European Topic Center on Land Cover (CEC, 1993). Germany was used for comparison as a large country for which the classes aggregated reasonably well to the UMd scheme. A graphic comparison of the UMd and CORINE Germany products can be seen in Figure 2.11c and 2.11d. The agreement between the maps at 1km, using a resampling of dominant cover type for the CORINE data into the 1km grid, is 65 percent for all pixels and 83 percent for those 1km grid cells with greater than 90 percent of one land cover type, showing that the core areas for the respective cover types have good agreement. Forest/non-forest comparisons agree 81% for the entire country and 92% when viewing only the 90% pure CORINE pixels. The agreement of needleleaf forests increases from 56 percent to 80 percent going from all pixels to just the 90 percent pure ones, while there is great confusion between mixed and broadleaf forests. Grasslands are poorly depicted in the north, revealing once again the limited ability to depict pasture within areas of intensive cropping. However, one-quarter of the CORINE grassland is labeled wooded grassland, mostly within areas of forest/grasslands mosaics in the south and west of the country.

2.3.4.3 NASA Landsat Humid Tropical Deforestation Pathfinder Project data at the University of Maryland

The University of Maryland's Pathfinder (Townshend et al. 1995) data sets for Colombia, Peru, Bolivia and the Democratic Republic of the Congo were examined in order to test the success of the UMd product in mapping tropical forest boundaries. The NASA Landsat Humid Tropical Deforestation Project depicts only a forest and non-forest layer, where forest represents humid tropical closed canopy forest and all other land covers are grouped as non-forest. The results for the South American data are shown in Figure 13a. The UMd product misses small clearings within the forest boundary and some montane forests, possibly due to the presence of clouds. One area of interest is southeast Bolivia where extensive tropical deciduous woodlands and forests are found. The UMd product has significant areas of this forest to the south trending into the Gran Chaco, where the Pathfinder product has none as these woodlands/forest are no longer a humid type formation. The agreements of 89.0, 91.8 and 82.0 percent for Colombia, Peru and Bolivia show the general success of the UMd product for this area in classifying tropical forest.

The Landsat Pathfinder data for the Democratic Republic of the Congo (Townshend et al. 1995) was examined in a similar fashion. Figure 2.13b shows this comparison. The overall agreement is 85.7 percent. The largest source of error is found within the forest boundary and in the eastern highlands. As stated earlier, depicting areas with persistence haze was found to be problematic. Training data from Equatorial Guinea and the Republic of the Congo created splits associated with cloud cover. However, these splits created problems in other areas of the globe, where cloudy signals were being mapped as broadleaf evergreen forest. As such, these splits were dropped from the trees, as the signals are not representative of a characteristic land cover. The result is a spotty depiction of forest cover within the central forest with problems increasing towards the Atlantic coast and Gabon. Within the context of Central Africa, these cloudy splits could be used for delineating likely forest in the central basin, along the Atlantic coast, and in the eastern highlands abutting the western rift valley.

2.3.4.4 Evaluation Summary

A number of conclusions can be drawn based on the comparisons made between the regional databases and the UMd product. The basic distinction between forest and non-forest shows good agreement with other sources, ranging from 81 to 92 percent. One area of possible improvement for the UMd map is the mapping of pastures within heavily agricultural areas. Future iterations of this product must include better training for this cover sub-type. Atmospheric degradation of the remote sensing signal in central Africa is difficult to handle in the global context and suggests the possible value of fusing other data sources such as radar in these areas.

Landscape heterogeneity found in high-resolution data sets is reduced in the 1km multi-temporal UMd product. Favoring the dominant classes when using coarser resolution data, especially the greener classes due to multi-temporal NDVI compositing, is in agreement with other findings (Moody and Woodcock 1994) and possible ways to reduce the loss of information for coarse scale maps are needed (Moody 1998). Using high-resolution data as a surrogate for ground truth may be a cost-effective way to characterize errors present in coarse scale maps (Kloditz et al. 1998).

2.3.4.5 Comparison with ground-based Food and Agriculture Organization forest statistics

United Nations Food and Agricultural Organization country forest statistics were compared with the UMd country totals for the three levels of canopy closure mapped in the classification system. The FAO statistics are provided by the individual countries and date from different years. An adjustment function was then used to estimate 1995 totals for all countries (FAO 1997). For developed countries, the FAO definition of forest describes areas with a minimum of 20% tree crown cover and for developing countries, a minimum of 10% tree crown cover. Although the definitions forest for FAO and the UMd data differ slightly, some conclusions can be made by comparing the internally consistent global 1km UMd product to statistics generated by individual countries.

Figure 2.14 shows plots of FAO forest versus UMd aggregate classes of forest (>60% canopy cover), forest plus woodland (>40%), and forest plus woodland plus wooded grassland (>10%). Overall the UMd aggregate class which best agrees with the FAO numbers globally is forest plus woodland, or areas with 40 percent and greater canopy closure. The UMd global totals for this aggregate are 11 percent higher than the FAO numbers, compared with being 80% higher when using all three woody classes combined and 37% lower using forest classed pixels alone.

However, it is clear that different definitions of forest are being applied in different countries. Others examining the FAO data set have found discrepancies due to different forest definitions, data sources and data processing (Mayaux et al. 1998). For example, many regional subsets of countries such as the those of the humid tropical Pan-Amazon, including Venezuela, Columbia, Peru and Bolivia, have FAO numbers which best agree with the forest numbers from the UMd map. On the other hand, many semi-arid nations of central Asia best agree with the aggregate of all woody classes, though their areas are too small to show in Figure 2.14. By taking the one UMd class aggregate which is closest to the FAO number (Figure 2.14d), the overall agreement between FAO global forest estimates and UMd estimates is reduced to a 7.0 percent lower figure for the UMd map compared to the FAO.

The continent with the highest disagreement between the two sources is Africa. By breaking the African countries into regional groupings, some disagreements can be reconciled when viewing the different canopy threshold aggregates. For a subset of humid tropical countries including Liberia, Sierra Leone, Cameroon, Equatorial Guinea, the Republic of the Congo, the Democratic Republic of the Congo, and Rwanda, the total disagreement, when comparing FAO forest (>10%

crown cover) to UMd forest (>60% canopy cover), is less than 1 percent: 1,562,270 kilometers squared to 1,577,816 kms^2. For these countries the FAO statistics do not appear to reflect the FAO definition of forest for developing nations, but are closer to measuring the UMd-defined forest subset of that definition. The disagreement jumps to 48 percent and then to 93 percent overestimations of forest cover when adding woodland and then wooded grassland totals to the UMd forest numbers. In general, it appears that countries with significant proportions of tall, dense forest are more likely to map this type of formation as the forested land, and not other less dense formations which still meet the FAO definition of 10% tree crown cover. On the other hand, countries such as Namibia, Botswana, Senegal, Mali and Niger appear to include sparser stands of trees such as that from the UMd wooded grassland class. For these countries, forest plus woodland UMd totals underestimate the FAO total by 97%, but by adding wooded grassland, the total disagreement is reduced to a 24% overestimation. This variable standard of woodiness can be discerned through the use of the global UMd land cover characterization.

The generation of internally consistent global classifications using remotely sensed data could be of help to users of data sets such as the one generated by FAO. The FAO's ground-based forest statistics represent a combination of various sources which could be brought into greater harmony through the use of remote sensing. For modelers and researchers interested in the human impacts of global change, an internally consistent approach to mapping land cover should prove valuable in standardizing the depiction of natural resources across regions, continents and the globe.

2.3.5 Constraints, Limitations and Assumptions

Performing global classifications of remotely sensed data provides for an internally consistent product which allows for the comparison of land cover between regions and continents. In this study, a 1km global land cover classification conforming largely to the IGBP class definitions has been made. A set of classification trees were created to map land cover using AVHRR 1km data from 1992-93. The minimum annual red reflectance metric proved very useful in delineating woody areas, while peak annual greenness was useful in describing leaf type. Temperature metrics were also used in discriminating tropical woodlands from forest, drought deciduous broadleaf forest from evergreen broadleaf forest, and in stratifying the tropics from temperate and boreal zones. Temperature also helped in separating shrublands from grasses and agriculture. Near-infrared metrics were helpful in separating crops from grass and shrub covers, and tropical inundated grasslands from woodlands. Many of the splits lend themselves to ready biophysical interpretations and point to the possibility of using the same tree for separate years in order to test the method's repeatability and for eventual use in detecting land cover change.

The classification trees also revealed the relatively few steps it takes to characterize most of the globe. However, many of the trees featured subtrees of considerable complexity, possibly related to the quality of the data. Future efforts using sensors such as MODIS will reveal the possibility of creating decision trees where a handful of splits successfully describes the entire globe. For the data used here, this was not possible.

All compositing methods available should be assessed for their utility in mapping land cover at coarse resolutions. NDVI compositing has been shown to be biased towards high view zenith angles in the forward scatter direction, preferentially binning on BRDF affected pixels. This has the effect of introducing geometrically distorted pixels, as well as making the derivation of true at-nadir reflectances difficult. The geometric distortions of pixels due to compositing methods was evident in the comparisons with high-resolution derived map products. Preliminary examinations of the UMd map to other AVHRR-derived maps using single date imagery (Zhu and Evans 1991 and Mayeaux et al. 1997) also show an increased blurring of the landscape due to the multi-temporal signals and maximum NDVI compositing. These characteristics of multi-temporal compositing imply that the map would more appropriately be made at a resolution greater than 1km, as the footprints of many pixels are actually considerably larger than the at-nadir size of 1.1km. Also, red and especially near-infrared values from the 1km data set are suspected to be greatly affected by BRDF effects and this limits the utility of these bands for certain areas and land covers. The resulting noisy time series for channels 1 and 2 complicates the use of these bands in classification. More robust approaches relying on one or more different compositing criteria should be used (Cihlar 1994; Lambin and Ehrlich 1996), along with corrective procedures (Cihlar et al. 1997), in order to avoid the typical problems associated with maximum NDVI compositing. Additionally, adding corrections for water vapor and aerosols will help create less noisy time series (Ouaidrari et al. 1997) and should allow for the creation of simpler classification trees.

2.4 Comparison of the IGBP DISCover and University of Maryland 1 km global land cover products

There are currently two global 1km resolution land cover products available derived from data from the Advanced Very High Resolution Radiometer, the first produced by the U.S. Geological Survey for the International Geosphere Biosphere

Programme and the second by the University of Maryland. This subsection is to compare the characteristics of these maps, the global IGBP Data and Information System DISCover and University of Maryland 1km land cover products. The reason for comparing these maps is to clarify the similarities and differences in the development of each product. A preliminary numerical comparison is also included to illuminate areas of agreement and disagreement. Both data sets were created for the same fundamental purpose of providing improved global land cover information for environmental modelers. The DISCover product was designed to meet the various global land cover needs of the IGBP core science projects (Rasool 1992; IGBP 1992). The IGBP-DIS Land Cover Working Group (LCWG) developed a program to create a global land cover product based on 1-km AVHRR data which culminated in the DISCover land cover product (Loveland et al., 1999). At the University of Maryland, global land cover maps have been produced for the modeling community and, as finer resolution global data sets have become available, for researchers working on a variety of applications requiring land cover information. Recent research has included the generation of one degree (DeFries and Townshend, 1994), 8 kilometer (DeFries et al. 1998) and 1 kilometer (Hansen et al., 1999) global land cover maps. As described by Merchant and others (1993), evaluating large area land cover products is very difficult. The primary reason for this difficulty is a lack of corroborating evidence and the relatively high cost of conducting a statistically meaningful validation. Existing regional land cover data that may be available for comparison are often of undocumented accuracy, developed with non-standardized classification legends, and developed with unknown methodologies. Using such information often only compounds the evaluation of global products. In lieu of a rigorous statistical validation, a comparative overview of the methodologies, along with areal and per pixel comparisons, is offered here to help users understand the differences between the products and allow them to make better informed decisions on how to use these data sets.

2.4.1 Methodological Similarities and Differences

Table 2.5 illustrates a number of similarities and differences between the two products. They each use data from the National Oceanic and Atmospheric Administration's (NOAA) AVHRR satellite sensor. The data derived from the AVHRR that were used in the two classification sequences were collected based on monthly maximum normalized difference vegetation index (NDVI) composites dating from April 1992 to March 1993 inclusive. The DISCover project used the 12 monthly NDVI data while the University of Maryland used all 5 AVHRR channels as well as the NDVI in deriving 41 multi-temporal metrics from the 12 monthly composites. The IGBP-DISCover product was created using the 12 monthly maximum NDVI values, representing the annual phenology of vegetation, as inputs into an unsupervised clustering program. The clusters resulting from the algorithm were then labeled and refined at the continental scale according to available ancillary digital and map-based information. Over 250 maps and atlases of ecoregions, soils, vegetation, land use, and land cover were used in the interpretation phase of the study and served as reference data to guide class labeling. This approach provided a highly flexible methodology in creating a product which best reproduced the thematic information in the ancillary maps while adding the spatial detail inherent in the remotely sensed data. For more information on the cluster refinement and labeling techniques see Loveland and others (1999).

The DISCover classes are of the IGBP classification scheme. A tabular comparison of the DISCover and UMd class lists can be found in Hansen et al. (1999). The processing sequence for the IGBP-DISCover product was continent-by-continent as the data became available through the IGBP-DIS global 1-km project (Eidenshink and Faudeen 1994). The DISCover product was released via the World Wide Web

http://edcwww.cr.usgs.gov/landdaac/glcc/glcc_na.html

free of charge to all potential users in July, 1997 and is scheduled to be improved twice yearly based on peer-review, user feedback, and results from the validation study.

Table 2.5 Similarities and Differences of the IGBP-DISCover and University of Maryland Global Land Cover Products

Product Characteristics	**IGBD DISCover**	**University ofMaryland**
Sensor	AVHRR	AVHRR
Time of Data Collection	April 1992 –March 1993	April 1992 – March 1993
Input Data	12 monthly NDVI composites	41 metrics derived from NDVI and Bands 1-5
Classification Technique	Unsupervised clustering	Supervised classification tree
Processing sequence	Continent-by-continent	Global
Classification Scheme	IGBP (17 classes)	Simplified IGBP (14 classes)
Refinement/Update schedule	Twice yearly	Currently being updated
Validation	September 1998	Evaluated using other digital data sets

The University of Maryland (UMd) used a supervised classification tree based on 41 temporal metrics calculated to represent the phenology of global vegetation.

Training sites were derived from over 150 interpreted Landsat scenes distributed throughout the world. A complete list of the Landsat training scenes, along with ancillary data used to interpret them, can be found at the University of Maryland web site

http://www.geog.umd.edu/landcover/global-cover.html

The UMd classes largely conform to the IGBP scheme. Not included in the UMd product are the permanent wetlands, cropland/natural vegetation mosaic and ice and snow IGBP classes. Signatures derived by the classification tree algorithm were extrapolated worldwide. Most signatures act globally, while others represent unique regional characterizations of a single class or subclass. The University of Maryland product is available at the previously mentioned website, and an improved future version will be generated based on evaluations using ancillary data and user feedback. The IGBP LCWG established a validation working group who developed a strategy and methodology for validating the DISCover land cover product (Belward 1996). The strategy is based on a stratified random sample of the DISCover land cover classes. The random samples were taken from higher resolution satellite imagery (mainly Landsat and SPOT). There is no formal validation program of comparable statistical rigor established for the University of Maryland product due to the considerable cost involved. As an alternative, comparisons with other regional digital data sets are being used to evaluate the map. The DISCover validation sites will also be used in this fashion. While these sites will not provide accuracy statements with known confidence levels due to the IGBP DISCover based sampling strategy, it will certainly provide valuable information.

2.4.2 Areal and per Pixel Comparisons

Figure 2.15 shows the areal totals for classes as aggregated into physiognomically similar groupings. The totals are quite similar, the only exception being the apparent disagreement in grass/shrub cover totals. This difference is explained by the absence of the agriculture mosaic class in the UMd classification. However, when comparing the per pixel accuracies for these groupings, it is clear that the internal arrangement of the classes as represented on the globe is quite different between the maps. The percent per pixel agreement for these groupings, excluding the agricultural mosaic and wetlands classes which do not nest into the UMd classes, is 74 percent.

Per pixel agreement and disagreement can be seen in Figure 2.16, which displays the agreement between the two maps for tall (forest and woody savanna/woodlands) and short/no vegetation (all other classes). As shown in

Figure 2.15, the overall areas for these classes differ very little. The global totals for tall vegetation differ by less than 1.6 million square kilometers or less than 4 percent of the total tall woody land cover as expressed in each map. However, the per pixel agreement for tall versus short vegetation is 84 percent. Figure 2.16 shows how most core forested areas are mapped similarly, while disagreements occur mostly along the edges of these areas and constitute wide regional variability. For example, West Africa in the DISCover map is woodier than in the UMd map, while the opposite is true in Southern Africa. Users whose models are sensitive to regional variability should be aware of these disagreements between the two products.

Figure 2.17 shows the areal totals for all classes and reveals two significant differences between the maps. First, while the aggregate forest/woody savanna and woodlands totals may be similar, the DISCover map has more forest, of all types, than the UMd map. The woody savanna/woodland class, conversely, has greater presence in the UMd map. Also, the wooded grassland class for the UMd map is over two times the size of its savanna counterpart in the DISCover map. Much of this disagreement is related to the mosaic class used in the DISCover product. The overall result from these two differences is the increased presence of intermediate woody classes such as woody savannas/woodlands and savannas/wooded grasslands in the UMd map than in the DISCover map. Excluding the three classes not present in the UMd map, the per pixel agreement for the remaining classes equals 48 percent. The fact that the agreements diminish greatly when viewing all of the classes versus aggregates is not surprising, but users who need this level of detail should examine the data themselves in order to judge which map is most useful for their purposes.

Three snapshots of local areas at full-resolution have been included to reflect the level of concurrency between the two maps. Figure 2.18a shows an area near Perth, Australia where both maps exhibit general thematic agreement with the consistent delineation of forest/woodlands and crops. Figure 4b is of an area along the United States/Canada border in the Pacific northwest where there is general agreement for the class aggregates of Figure 2.15, but confusion within the aggregates themselves. There is disagreement within the forested area between evergreen needleleaf and mixed forests and between the open shrublands and grasslands of the Columbia River basin. The increased presence of forest in the DISCover map and of intermediate tree cover classes within the UMd map can also be seen along the forest/non-forest boundaries. Figure 2.18c is an example in France of the identification of the same geographic entity, the Massif- Central, but of two different thematic depictions due to the use of different classification schemes. The absence of the cropland mosaic class in the UMd map creates a significant divergence in the portrayal of this area for both maps. The DISCover map characterizes the area as an agricultural mosaic, while the UMd map has forests, woodlands, wooded grasslands and croplands present. At coarse resolutions, mixed pixels dominate in many areas such as Europe, and a consistent characterization between maps can be difficult to realize. Not having a common classification scheme assures dissimilar depictions and creates problems for evaluators and users.

2.4.3 Comparison to ground-based maps

One of the primary reasons for developing remotely sensed derived land cover maps is the ability to improve upon traditional ground-based mapping methods. DeFries and Townshend (1993) revealed the level of disagreement present among traditional ground-based land cover maps and advocated the use of remote sensing to map global land cover as a way to create more consistent map products. A comparison of the agreement between the remotely sensed derived DISCover and UMd maps with two land cover maps derived from ground-based data revealed a gain in thematic agreement. Two maps, the "Global Distribution of Vegetation at 1øX1ø" compiled by Matthews (1983) and "Carbon in Live Vegetation of Major World Ecosystems" by Olson et al. (1983) were examined to make this comparison. The nesting of the data sets into individual classes allowed for a number of possible permutations, so each ground-based map was aggregated into the classes present in Figure 2.15. Of these classes, the forest/woodland, grass/shrubs, crops, and barren classes are common to all four maps. The Olson and Matthews maps were reprojected into the Interrupted Goode Homolosine projection and the 1km data sets were resampled to this coarser grid. The results comparing the Matthews/Olson and DISCover/UMd agreement are shown in Table 2.6.

The ground based maps have an average class disagreement of 33.7%, while the same number for the remotely sensed derived maps is 18.1%, indicating a reduction in the areas of disagreement by 46%. The overall disagreement is reduced by 38%. However, these are not measures of accuracy. In fact, two maps could have 100 percent agreement and be entirely wrong. It is posited here that the synoptic view provided by remote sensing allows for a more consistent depiction of the earth surface than do traditional approaches, even when given the greatly disparate classification approaches used in the making of the DISCover and UMd maps.

Table 2.6 Comparison of thematic agreement at nominal 0.5 degree resolution grid of remotely sensed derived DISCover and UMd maps and ground-based "Global Distribution of Vegetation at 1º x 1º" compiled by Matthews (1983) and "Carbon in Live Vegetation of Major World Ecosystems" by Olson et al. (1983).

DISCover/ UMd	**Forest/ woodland**	**Grass/shrubs**	**Crops**	**Bare ground**
Forest/woodland	88.6%	9.0	2.4	0.0
Grass/shrubs	15.8	69.0	10.0	5.2
Crops	8.6	12.2	79.2	0.0
Bare ground	0.0	9.3	0.0	90.7

Average class agreement = 81.87%
Overall agreement = 80.32%

Olson/Matthews	**Forest/ woodland**	**Grass/shrubs**	**Crops**	**Bare ground**
Forest/woodland	70.2%	22.0	71.	0.7
Grass/shrubs	14.9	60.0	6.7	18.5
Crops	16.1	29.5	51.1	3.2
Bare ground	0.5	14.6	1.0	83.9

Average class agreement = 66.3%
Overall agreement = 68.35

2.4.4 Discussion and Conclusions on the Comparison

The approaches each research group has taken to complete the task of characterizing the globe into a set of similar classes are very different. From the algorithms to the input variables, there is little in common between the two methods. However, while many differences do exist, there is an amount of thematic agreement present, especially at the class aggregate level Aside from the input variables, algorithms and classification schemes, a number of external factors create variability which make it difficult to clearly compare the methodologies.

One important variable is the reliance on a wide and varying set of ancillary data sources within both techniques (DeFries et al. 1998). For the DISCover product, ancillary sources were used to label clusters resulting from the unsupervised classification algorithm. For the UMd map, ancillary sources were used to aid in interpretation of the original high-resolution data sets which, in turn, were used to create the 1km training data set. Regional variability in the quality and reliability of these data sources is very high and introduces variability in the output map products. The IGBP LCWG validation workshop is a first step in attempting to generate a standardized global validation data set for use with coarse resolution maps. The production of such data sets makes it possible to test the differences between the methodologies by providing a global reference standard.

Another variable is the 1km data set, which is also a first generation product. Artifacts exist within these data due to a variety of factors which, in turn, can differentially affect the map outputs. The presence of clouds, data gaps, misregistrations, and other anomalies increase the probability of errors being portrayed in the final land cover products. The extent to which noisy data are manifested or ignored within the two mapping approaches and, thus, in the final maps is currently unknown. A more rigorous comparison of the two maps would include a discussion of the degree to which the two approaches handle noisy data. Future production of global data sets will employ new techniques for generating global satellite composites which will reduce many of the undesired effects associated with past approaches (El Saleous et al. 1999), and allow for comparisons relating classification methodologies directly to multi-spectral information.

The IGBP DISCover and the University of Maryland 1km land cover products represent the first ventures into mapping global land cover at a moderate spatial resolution. Questions regarding appropriate methodologies, data sources, and evaluation techniques are still under investigation. The future task is to discern areas of weakness within the present set of products and identify ways to produce improved iterations of these maps. This first review shows general agreement for broad vegetation categories, with low per pixel agreement for individual classes and significant regional variability. Answering why the disagreements exist and how to improve correlation between maps is an important research topic and might include the identification of core areas for major land covers, areas of mixed pixels, and the identification of multi-spectral information which bests discriminates global land covers.

3. The MODIS Global Land Cover Change Indicator Product at 250m Resolution

3.1 Introduction

The earth's land cover exerts an important control on the planet's environment. Land cover influences surface roughness and albedo which consequently affect exchanges of sensible heat, water vapor (latent heat), and carbon dioxide and other greenhouse gases between land surface and the atmosphere. In addition, the vegetation plays a physiological role in these exchange processes through stomatal resistance and photosynthetic capacity (Sellers et al., 1996). These exchanges of energy and materials are major components of the hydrologic cycle, the carbon cycle, and the global climate system. Consequently, many hydrological, ecological, and climatological models use geographically referenced land cover information as an essential input (Asrar et al, 1994; Denning et al, 1996). Reliable land cover information is thus increasingly recognized as having crucial relevance for understanding many aspects of earth system science (Townshend et al., 1991, 1994). The significant effects of hypothetical land cover changes on the climate (Dickinson and Henderson-Sellers, 1988; Nobre et al., 1991; Yukuan et al, 1994; O'Brien, 1996; Xue, 1996) indicate that land cover change information is also important for global change studies. As earth system models become more sophisticated, it will be necessary to incorporate land cover change as a variable. In addition, monitoring land cover change is increasingly important for natural resource management, biodiversity assessments, and inventories for implementing international agreements on greenhouse gas emissions.

3.2 Overview and Technical Background

Several static global land cover products derived from remotely sensed data are available or under production (Loveland et al., 1991, 1997; DeFries et al., 1994, 1995, in press; Hansen et al., 1999). These products were created primarily with remote sensing data from NOAA's Advanced Very High Resolution Radiometer (AVHRR). The Moderate Resolution Imaging Spectroradiometer (MODIS) of NASA's Earth Observing System (EOS) will provide an improved source of global information for the study of land surfaces with spatial resolutions of 250 to 1000 meters depending on the bandwidth. As one of the efforts of the MODIS Land Science Team, a global land cover change product at 1 km resolution will be created by Boston University to depict broad-scale land cover changes attributable, for example, to interannual variability in climate (Lambin & Strahler, 1994). The University of Maryland will provide a product at 250m resolution to depict land cover changes due to anthropogenic activities which generally occur at finer resolutions than 1 km (Townshend et al., 1991). This document describes the 250m resolution land cover change product developed by the University of Maryland. Specifically, this section presents the generation procedure, the change detection algorithms and the associated look up tables (LUTs) required for their implementation, the data sets used for creating the LUTs and testing the change detection algorithms, and finally the results of the algorithm testing.

The MODIS instrument onboard the EOS AM-1 platform is a scanning radiometer system with 36 spectral bands extending from the visible to the thermal infrared wavelengths (Running et al, 1994). The first seven bands are designed primarily for remote sensing of the land surface with spatial resolutions of 250m for bands 1 (red, 620-670 nm), and band 2 (near infrared, 841-876 nm), and 500m for bands 3 to 7 (459-479nm, 545-565nm, 1230-1250nm, 1628-1652nm, 2105-2155nm, respectively). Its orbital configuration and its viewing geometry produce full global coverage every two days. Because a very high proportion of land cover changes due to human activities occur at spatial scales around or less than 250 meters (Townshend et al, 1991), the land cover change product described in this document is derived from the only two bands available at 250m resolution. Although the number of the available bands is limited, the two bands are in the red and near infrared wavelengths, the most important spectral regions for remote sensing of vegetation (Townshend and Justice, 1988).

Considering that both the information available in the two 250m bands of MODIS and the current scientific knowledge in global scale land cover change detection are limited, the MODIS 250m global land cover change product is designed to serve as an alarm system rather than a comprehensive global scale land cover change monitoring system. This alarm system would provide users with indicators for where the major land cover changes might have occurred and then users can use higher resolution remote sensing data of the indicated areas to examine the exact locations and types of the changes. One of the direct applications of the alarm product is to help the data acquisition strategy of the Landsat 7 satellite. With this alarm system, we aim to identify those changes that are caused by human activities, such as deforestation, urbanization, agricultural expansion or contraction, as well as by extreme natural events, such as flooding and fire (burn scars). Specifically, the types of land cover change to be detected in this at-launch version of the product are conversions between the following land cover types: Forest (tall woody vegetation with greater than 40 percent canopy cover), Non-forest (short herbaceous vegetation or woody vegetation with less than 40 percent canopy cover), Bare ground, Water bodies, and Burn scars (Table 3.1). These simplifications are associated with the conservative goal of the current at-launch version of the product. Once experience of detecting global scale land cover change with real MODIS data is gained, other detailed types of land cover change, such as conversions between non-forest land cover types will be included in the post-launch version of the product.

Table 3.1 Types of land cover change to be detected by the MODIS 250m land cover change product. The empty boxes indicate that the conversion is not of interest or is not likely to occur.

Time 1 Cover Type	Time 2 Cover Type				
	Forest	Non-forest	Bare	Water	Burn
Forest	-	Deforest.	Deforest.	Flooding	Burn
Non-Forest	Regrowth	-	Urban.	Flooding	Burn
Bare	Regrowth	Agricul.	-	Flooding	-
Water	Flood retreat	Flood retreat	Flood retreat	-	-
Burn	Regrowth	Regrowth	-	-	-

Figure 3.1 shows the data processing scheme for the 250m global land cover change product. The processing procedure takes advantage of the gridded level 2 (L2G) products of surface reflectance for the two 250m bands. The L2G surface reflectance product used as input in the processing chain has been atmospherically corrected for molecular scattering or absorption of atmospheric gases (such as water vapor, carbon dioxide, ozone, and other trace gases), aerosols, and thin cirrus clouds (Vermote et al., 1995, 1997). We chose to use a surface reflectance product that does not employ a bidirectional reflectance distribution function to correct for sensor geometry in order to avoid assumptions about land cover type.

The first step in the processing chain involves compositing the surface reflectance for each 32 day period to maximize the availability of cloud-free, snow-free, good quality and close-to-nadir surface reflectance data. The compositing procedure we have chosen is shown in Figure 3.2. After the 32-day surface reflectance data for the red and NIR bands have been generated for the two dates to be considered, they are used as input to five change detection algorithms. In the absence of MODIS data for developing and testing the algorithms, we use multiple algorithms to build confidence in the result. The change results from the five algorithms are then integrated with an “algorithm integration rule” to determine whether to label the pixel as “change” or “no change.” The five change detection algorithms and the algorithm integration rule are described in section 3.

The 250m global land cover change product detects changes between images acquired at both three month and annual intervals. For the three month interval, which is confounded by phenological changes that do not represent a change in cover type, we apply the algorithms to three pairs--a one month interval, two month interval, and three month interval--in order to build confidence in the result (see Figure 3.3). These three results are then integrated into a final result for the three month period using the time integration rules that combine the various outcomes for the three time intervals.

3.3 Algorithm Description

3.3.1 Theoretical Description of Change detection Methods

Detection of land cover changes has been a major application of remote sensing for more than a decade. During this time period, the role of remote sensing in monitoring the earth’s environment became emphasized (Townshend, 1977). Several change detection techniques have been developed and applied. These techniques fall into two categories: analysis of differences in classification results between two dates, and analysis of radiometric differences between dates. In the absence of very high accuracies in classification results, the classification approach must be used cautiously in order that misclassified pixels in either of the two dates are not erroneously labeled as change. Radiometric methods include band differencing, band ratioing, transformed band differencing, principal component analysis, and multispectral or multitemporal change vector analysis (see Singh, 1989 for a review and Johnson and Kasischke, 1998 for examples). Although these methods have been successful with the local-scale samples to which they have been applied, none of them have been tested at a global scale. Because MODIS data will not be available until the EOS-AM1 platform is launched, it is only possible to develop and test the algorithms with simulated data. For this reason, we employ multiple change detection methods in the 250m MODIS land cover change product in order to have a reasonable level of confidence in the result.

Specifically, the change detection methods used in the 250m MODIS land cover change product are: the red-NIR space partitioning method, the red-NIR space change vector method, the modified delta space thresholding method, changes in the coefficient of variation, and changes in linear features. The first three methods exploit the spectral information from MODIS bands 1 and 2 for the two 32-day composites being compared. The other two methods exploit changes in spatial texture. We describe the theoretical basis for each of the methods in the following sections.

3.3.1.1 The red-NIR space partitioning method

Most land cover changes caused by human activities, flood or fire are associated with changes in the surface brightness and greenness. Therefore, the locations of a pixel in the two dimensional space of brightness and greenness at different times should indicate whether and what type of change has occurred. Because the brightness can be represented by albedo (approximately the mean of MODIS bands 1 (red) and 2 (near infrared) reflectances), and the greenness can be represented by the difference between MODIS bands 2 and 1, the brightness-greenness space is just a 45 degree clockwise rotation of the red and NIR space (Figure 3.4). In addition, the value of the Normalized Difference Vegetation Index (NDVI) of a point in the Red-NIR space is associated with the slope of the line connecting the origin and the point. All points on one line going through the origin have the same value of NDVI. For a given geographic region and time of year, the spectral signatures of various land cover types have characteristic ranges in the red-NIR space. The red-NIR space partitioning method exploits these characteristic land cover signatures to detect change (Hansen et al., 1998).

The method partitions the red-NIR space into five classes: forest (tall woody vegetation with greater than 40 percent canopy cover), non-forest (short herbaceous and woody vegetation with less than 40 percent canopy cover), bare ground, water bodies, and burn scars. By comparing the locations of the pixel in the red-NIR space at time 1 (the composite derived from 32 daily observations for the first month being considered) and time 2 (the composite derived from 32 daily observations for the second month being considered), we can determine whether conversions between the five cover types have occurred. Though similar to the classic classification difference method, this method differs in the following important ways: 1) it distinguishes only five classes which are spectrally distinct compared with more detailed land cover classifications, and 2) it labels pixels as changed only when it migrates in spectral space from the core area for one cover type in time 1 (the spectral space with no confusion between classes, see section 5.1 for further explanation) to the core area for another cover type in time 2. Migration between a core area and an area in spectral space that represents mixtures of cover types are not labeled as change. This avoids the problem of overestimating pixels that have changed, a problem with classic classification differencing methods. To implement the red-NIR space partitioning method for the 250m land cover change product, a set of look up tables (LUTs) to define the core areas are needed. Section 5 describes the generation of these LUTs.

3.3.1.2 The red-NIR space change vector method

The red-NIR space change vector method is based on the presumption that land cover conversions can be characterized by a vector indicating a pixel's change in location in the red-NIR space from time 1 to time 2. The starting and ending positions, direction, and magnitude of the change vector are used to determine if and what type of change has occurred. In other words, the change vector method uses both the state and dynamic information of location in the red-NIR space compared with known spectral signatures of the five cover types (Figure 3.5). For example, if a forest does not undergo conversion between time 1 and time 2 and the seasonal change is not significant, the spectral signature does not change substantially and the change vector has a magnitude of zero or close to zero. If the forest is cleared for agriculture or urban development and becomes bare ground, then the change vector would generally move from low brightness and high greenness to high brightness and low greenness, in other words parallel with the red axis in the red-NIR space. If the forest is burned, both the greenness and brightness decrease and the corresponding change vector moves parallel but in the negative direction to the NIR axis in the red-NIR space. These examples illustrate the utility of the dynamics of the change vector, the magnitude and direction, for identifying land cover change. However, the change vectors associated with different types of change may have similar values for magnitude and direction, as shown in Figure 3.5 for changes from forest to bare ground and non-forest vegetation to bare ground. In this case, the state information, i.e. the starting and ending positions of the change vector, can indicate the type of change (Huang et al., 1998; Zhan et al., 1998).

The red-NIR change vector method differs from the traditional multispectral or multitemporal change vector methods (e.g., Malila, 1980; Colwell & Weber, 1981; Lambin & Strahler, 1994; Johnson & Kasischke, 1998) in that the former: 1) uses the starting or ending position of the vector in addition to magnitude and direction, and 2) distinguishes the characteristic signatures for different types of change using a decision tree approach (see section 5.2) rather than simply setting a threshold for the change magnitude and/or direction.

The magnitude A and direction θ of the red-NIR space change vector are computed from the reflectance values of Band 1 and Band 2 at time 1 and time 2 with the following equations:

$$A = \sqrt{(\Delta r_{\mathrm{Re}\,d})^2 + (\Delta r_{NIR})^2}\ . \tag{3.1}$$

$$q = \begin{cases} q_0\,, & \text{if } \Delta r_{\mathrm{Re}\,d} \geq 0 \text{ and } \Delta r_{NIR} > 0; \\ 90^{\circ}, & \text{if } \Delta r_{\mathrm{Re}\,d} > 0 \text{ and } \Delta r_{NIR} = 0; \\ 180^{\circ}\text{-}q_0\,, & \text{if } \Delta r_{\mathrm{Re}\,d} > 0 \text{ and } \Delta r_{NIR} < 0; \\ 180^{\circ}+q_0\,, & \text{if } \Delta r_{\mathrm{Re}\,d} \leq 0 \text{ and } \Delta r_{NIR} < 0; \\ 270^{\circ}\,, & \text{if } \Delta r_{\mathrm{Re}\,d} < 0 \text{ and } \Delta r_{NIR} = 0; \\ 360^{\circ}\text{-}q_0\,, & \text{if } \Delta r_{\mathrm{Re}\,d} < 0 \text{ and } \Delta r_{NIR} > 0; \end{cases} \tag{3.2}$$

where

$$q_0 = \arctan\left|\frac{\Delta r_{\mathrm{Re}\,d}}{\Delta r_{NIR}}\right|; \tag{3.3}$$

$$\Delta r_{\mathrm{Re}\,d} = r_{\mathrm{Re}\,d}^{\ T2} - r_{\mathrm{Re}\,d}^{\ T1}; \tag{3.4}$$

$$\Delta r_{NIR} = r_{NIR}^{\ T2} - r_{NIR}^{\ T1}; \tag{3.5}$$

and r_{Red}^{T1}, r_{NIR}^{T1}, r_{Red}^{T1}, and r_{NIR}^{T1} are the surface reflectance values of the MODIS band 1 (red) and band 2 (NIR) at time 1 (T1) and time 2 (T2), respectively. When the values of r_{Red}^{T1}, r_{NIR}^{T1}, r_{Red}^{T1}, and r_{NIR}^{T1} are available and the values of A and q are computed, the red-NIR space change vector method is implemented with a set of LUTs. The LUTs provide the ranges for values of A, q, r_{Red}^{T1} or r_{Red}^{T2}, and r_{NIR}^{T1} or r_{NIR}^{T2} associated with the various types of land cover change. The generation of these LUTs is described in section 5.

3.3.1.3 The modified delta space thresholding method

Because the seasonal changes of vegetation are not among the types of land cover change we are interested in, we apply the modified delta space thresholding method to compensate for seasonal differences in order to avoid flagging phenological variations as real change (Zhan et al., 1998). The change vector in the red-NIR space can be converted to the delta_red ($\Delta r_{\mathrm{Re}\,d}$) and delta_NIR ($\Delta r_{NIR}$) space (called the delta space for short) where delta represents the difference in reflectance between time 1 and time 2. With this conversion, the change vectors for all pixels start at the origin (Figure 3.6). The delta_brightness and delta_greenness space can be overlain with the delta_red and delta_NIR space, which aids the interpretation of the change vectors in terms of the types of changes they represent. The modified delta space is measured in the coordinate system of $dr_{\mathrm{Re}\,d}$ and dr_{NIR} which are the $\Delta r_{\mathrm{Re}\,d}$ and Δr_{NIR} modified to account for the expected seasonal variability in the reflectances. Mathematically, if the time 1 and time 2 averages of the red and NIR reflectance for the cover type of the pixel are M_{Red}^{T1}, M_{Red}^{T2}, M_{NIR}^{T1}, and M_{NIR}^{T2}, respectively, then

$$
\begin{aligned}
dr_{Red} &= \Delta r_{Red} - (M_{Red}^{T2} - M_{Red}^{T1}); \\
&= r_{Red}^{T2} - r_{Red}^{T1} - (M_{Red}^{T2} - M_{Red}^{T1}); \qquad (3.6) \\
dr_{NIR} &= \Delta r_{NIR} - (M_{NIR}^{T2} - M_{NIR}^{T1}); \\
&= r_{NIR}^{T2} - r_{NIR}^{T1} - (M_{NIR}^{T2} - M_{NIR}^{T1}). \qquad (3.7)
\end{aligned}
$$

With this seasonality compensation, the effects of fluctuations in reflectance associated with the seasonal changes are theoretically eliminated. Values of dr_{Red} and dr_{NIR} significantly larger than zero indicate real land cover changes.

For the MODIS 250m land cover change product, the modified delta space thresholding method is employed to label whether and what type of change has occurred with the following steps: 1) determine the cover type for each pixel using bands 1 and 2 reflectances with a set of "cover type" LUTs which are the ranges of the Band 1 and Band 2 reflectance values at the time 1 for each of the five cover types; 2) compute the values of dr_{Red} and dr_{NIR} with equations (3.6) and (3.7); 3) compute A and q by substituting the Δr_{Red} and Δr_{NIR} in Eqs. (3.1)-(3.3) with dr_{Red} and dr_{NIR}, and 4) determine whether change has occurred and type of change from the computed A and q in conjunction with the "change" LUTs for the cover type determined in step 1. The "cover type" LUTs and the "change" LUTs are described in section 5.

3.3.1.4 The texture change detection method

Texture features describe the spatial distribution, or heterogeneity, of the reflectances within one or in a combination of multiple bands. Information about the spatial distribution complements information available from spectral features (Strahler, 1981). Most land cover changes that we aim to detect with this product correspond to a change in texture features. For example, deforestation caused by logging or farming generally increase heterogeneity of the deforested areas along the boundaries of the deforested areas. Agricultural expansion in the desert also increases the heterogeneity of the landscape.

Many measures of texture features have been proposed (Wulder et al, 1998; Lambin, 1996; Mayaux and Lambin, 1996; Haralick, 1979). After applying some of these measures to the test data sets, we find that the coefficient of variation (CV: standard deviation divided by the mean) using NDVI values of neighboring pixels in a 3 by 3 pixel kernel to be an effective texture measure for change detection. For the at-launch version of the 250m MODIS land cover change product, we use the following criteria to label changed pixels: If $|CV_{T2} - CV_{T1}| >= 4$, then label the pixel as changed, where CV_{T1} and CV_{T2} are the values of CV for NDVI in a 3 by 3 pixel kernel surrounding the pixel at time 1 (T1) and time 2 (T2), respectively.

3.3.1.5 The linear feature change detection method

The linear feature change detection method is based on the observation that many land cover changes caused by human activities are associated with an explicit boundary such as roads, power line right-of-ways, or the edges of fields. If a linear feature is observed at time 2 but was not present at time 1, it can be inferred that change has occurred.

The linear feature change detection method has three steps: 1) highlight linear features by manipulating the gray levels of neighboring pixels with an edge enhancement method; 2) identify linear features in both the time 1 and time 2 edge-enhanced images; and 3) label the pixel as changed if a linear feature is identified in time 2 but not time 1.

Exploratory analysis identified band 1 (red) reflectance as better at discriminating linear features than either band 2, or metrics based on combinations of bands 1 and 2. The step 1 edge enhancement of band 1 reflectance computes the mean of the absolute difference between the gray level value at each pixel and at each neighbor in a 3 by 3 image kernel surrounding the pixel. In Step 2 a continuous indicator of the presence of a linear feature is derived using the following rule: in each of the four directions through the center pixel in a 3 by 3 image kernel, find the minimum edge enhanced value, then save the maximum of these four minimum values. Step 3 identifies the pixel as containing an edge if the result of step 2 is greater than or equal to 3.7, and then labels the pixel as changed if an edge exists in time 2 but not time 1.

3.3.2 Data Sets for Implementing and Testing Change Detection Methods

The 250m MODIS land cover change product will be generated from data acquired by MODIS bands 1 and 2 using the change detection algorithms described above. However, to derive the LUTs required by the algorithms to develop this at-launch product, a global data set of the red and NIR surface reflectances are needed before real MODIS data are available. Also, to test the performance of the change detection methods, simulated MODIS data for test sites are needed. For these purposes, we use two types of existing remotely sensed data. First, the LUTs for the three spectral methods (the red-NIR space partitioning method, the change vector method, and the modified delta space thresholding method) were generated mainly using data from the Advanced Very High Resolution Radiometer (AVHRR) together with spectral data from Landsat

Thematic Mapper (TM). Second, the testing of the five change detection methods was conducted with data sets simulated from Landsat TM image pairs. The following sections describe these data sets.

3.3.2.1 AVHRR data sets

The AVHRR sensor is a relatively simple scanning radiometer with five bands in the red, NIR, and thermal spectral regions (Kidwell, 1988). It is a "heritage instrument" of MODIS with an orbital configuration and viewing geometry producing daily full earth coverage. The AVHRR red (channel 1: 580-680 nm) and NIR (channel 2: 725-1100 nm) bands overlap the MODIS red (band 1: 620-670 nm) and NIR (band 2: 841-876) bands but have larger bandwidths than the MODIS bands. Similar AVHRR sensors on board NOAA's satellite series have been continuously observing the earth's surface since 1981. The historical record has been preserved in an archive to produce continuity needed for land surface studies. Many efforts have been made to calibrate and atmospherically correct the data, such as NASA's AVHRR Land Pathfinder project (Agbu and James, 1994; James and Kalluri, 1994). The AVHRR Pathfinder data are calibrated and corrected for the atmospheric effects of molecular, aerosol, trace gas absorption and scattering. However, they were not corrected for water vapor absorption. Because no other remotely sensed and atmospherically corrected red and NIR surface reflectance data are available globally, we used the AVHRR Land Pathfinder data for generating the LUTs of the change detection algorithms.

Two sets of AVHRR data were used for generating the LUTs: the 8km data for 12 years from 1982 to 1993 (Agbu and James, 1994) and the 1km AVHRR data for 1992-93 (Eidenshink and Faudeen, 1994). The 1km data set has closer spatial resolution as MODIS and a 1km pixel should have better purity than an 8km pixel. However, the 1km data set has more cloud contamination than the 8km data sets. Since each of the two data sets has advantages and disadvantages, we use both for the prototypes of the LUTs needed for the change detection method at this stage when we do not have better data available. We composited the decadal 8km and 1km data to monthly values based on maximum NDVI values (Holben, 1986). In order to derive representative red and NIR reflectances from the 12 years of the 8km data, for each month we ranked the values from low to high near-infrared reflectances. Then, the value least likely affected by both atmospheric and bidirectional effects (the one gave the composite image with the least speckles) was chosen for each month. The corresponding red and NIR reflectance values for that year were then extracted to construct a representative monthly data set of red and NIR reflectances.

Pixels sampled from the 8km and 1km AVHRR data were subsequently used as training data to construct the LUTs. This will be described in section 3.3.3.

3.3.2.2 Landsat Thematic Mapper (TM) data

Landsat TM data were used for two purposes: 1) to extract sample reflectance values in the red and NIR bands for water bodies and burned areas and 2) to test the change detection methods. Landsat TM has seven spectral bands ranging from the visible blue-green to the thermal infrared spectral regions. Band 3 (red: 630-690 nm) and band 4 (NIR: 750-900 nm) of Landsat TM are the "heritage bands" of the MODIS bands 1 and 2 and can be used to simulate MODIS data. The pixel size of the TM images for the red and NIR bands is 28.5 m. Landsat 4 and 5 have a 705 km near-circular, sun-synchronous orbit with a repeat period of 16 days. Global coverage of Landsat data is not available. However, we selected cloud-free TM images or image subsets in several locations for use in the development of the change detection algorithms.

A TM image of an area in northeastern China where a boreal forest had been burned massively was used to extract the sample values of red and NIR reflectances for burn scars. The sample reflectance values for water bodies and flooding were obtained from TM images of the Washington, DC area; Manaus, Brazil; and the San Francisco Bay area. We delineated polygons to identify water bodies, floods, and burn scars. The TM images were then degraded to MODIS 250m resolution using a specially designed filter that approximates the point spread function of MODIS (The computer code for this transformation was obtained from Dr. Kai Yang and is referred to as TM-MODIS code hereafter). The reflectance values of the delineated areas on the simulated MODIS images were extracted to represent red and NIR values of water and burn scars. The seasonal variations of these reflectance values were considered to be negligible.

To validate the change detection methods presented previously, more than a dozen pairs of cloud-free or near cloud-free Landsat TM images have been obtained for different locations around the world where various types of land cover conversions are occurring. The characteristics of some of these locations are listed in Table 3.2. To reduce the size of document, only three pairs of these data sets, representing agricultural encroachment into desert, agricultural expansion into tropical rainforest, and temperate urban development, are going to be presented.

To utilize these TM image pairs for testing the performance of the change detection methods, preliminary data processing is required. The most important processing requirements for change detection are the accurate registration and the radiometric normalization of the images. As the first step, the original TM image pairs were coregistered using ground control points. A root mean square error (rms) less than 0.67, corresponding to approximately 20m, was achieved using a linear or second order polynomial equation. The TM data were then degraded to the MODIS spatial resolution of 250m using the TM-MODIS code. Based on the rms of 20m for the TM data, the rms of the coregistration of the simulated MODIS data is less than 0.1 pixel.

Radiometric normalization of the test data is of equal importance to geometric registration. We applied a radiometric normalization procedure based on Hall et. al (1991) to most of the pairs of coregistered, simulated MODIS data. For each pair of images, black target pixels such as water bodies and bright target pixels such as bare soil were selected. If their reflectance values at time 1 and time 2 were significantly different (more than 5 percent of the mean value), we determined that the pair of data required radiometric normalization and the procedure was applied. For the three pairs of data listed in Table 3.1, the Washington, DC and Egypt pair were normalized. The Bolivia pair was not because the dark and bright target reflectance values were comparable.

For each test data pair, we delineated by visual inspection where land cover change had occurred using the original TM images. The change bitmaps at TM resolution were then converted to 250m using the TM-MODIS code. If the 250m simulated MODIS pixel included at least 25 percent change based on the TM resolution change bitmap, the 250m pixel was labeled as change. These change bitmaps at MODIS resolution were used to test the performance of the change detection methods (section 6).

Table 3.2 Characteristics of the Landsat TM images used for creating test data sets (* indicate the data set is presented in this document)

Location	Dates of TM images	Main types of land cover change
*Alexandria, Egypt	June 7, 1984 June 13, 1992	Agricultural expansion in desert
Charlotte, NC	July 8, 1984 July 28, 1997	Temperate mixed woodland to urban development
Manaus, Brazil	Aug. 2, 1989 Sept. 20, 1995	Conversions between forest and non-forest and between water and land
Orlando, FL	Jan. 9, 1985 Jan. 26, 1997	Forest to agricultural fields or Residential areas
Ontario site 2, Canada	Aug. 17, 1985 Aug. 20, 1992	Boreal forest deforestation and regrowth
Ontario site 3, Canada	July 27, 1987 July 3, 1996	Boreal forest deforestation and regrowth
Rondonia, Brazil	Aug. 10, 1986 July 20, 1996	Tropical rain forest to agricultural fields
*Santa Cruz, Bolivia	July 2, 1986 July 10, 1992	Rain forest to agricultural use
Parana River Basin, Brazil	Nov. 22, 1986 Nov. 20, 1991	Patches of forest converted into agricultural fields
*Washington, DC	May 26, 1985 May 8, 1990	Temperate mixed woodland to urban development
Yellowstone, WY	Sept. 22, 1987 Oct. 10, 1988	Forest to burn scars
Yucatan, Mexico	April 14, 1986 April 4, 1994	Urban growth in arid or semiarid area

3.3.3 Implementation of the change detection methods

For the generation of the 250m MODIS land cover change product, the five algorithms are implemented with look up tables (LUTs). To account for the seasonality differences between the latitudes, the earth is split into four regions: the north region (>23.5 degrees N), northern tropical region (0-23.5 degrees N), southern tropical region (0-23.5 degrees S) and south region (>23.5 degrees S). The LUTs associated with each of the five methods were created for each of these four regions and for each of the 12 months. Thus, for each of the five methods, there are 12 x 4 = 48 LUTs. These LUTs were designed and generated as follows.

3.3.3.1 LUTs for the red-NIR space partitioning method

The LUTs for implementing the red-NIR space partitioning method are a set of tables which determine the land cover class membership from the red and NIR reflectance values. They are used according to the following mathematical function:

$$Cover\_Type\ (r_{Red}\ ,\ r_{NIR}) \qquad (3.8)$$

where r_{Red} and r_{NIR} are the surface reflectance values of MODIS bands 1 and 2 respectively, and the values of the function is one of the following cover types: forest, non-forest, bare, water, burn scar and mixtures of each. These functions are determined for each of the four latitude regions for each of the 12 months.

To determine the values for the LUTs, we used decision trees, a technique described by Breiman et. al (1984) and implemented for land cover classification using remotely sensed data (Hansen, 1999; Hansen et al., 1996; DeFries et al., in press; Friedl & Brodley, 1997). Decision trees predict class membership by recursively partitioning training data into more homogeneous subgroups. A deviance measure is calculated for all possible splits in the training data and the split that yields the greatest overall reduction in deviance is chosen to partition the data. The procedure is repeated with the subgroups until a decision tree is created with terminal nodes with no misclassification errors or until preset conditions are met for terminating the tree's growth. By selecting those terminal nodes with no misclassification errors (pure nodes), we identified the spectral signature in the red-NIR space for the "core area" for each cover type. Terminal nodes with high classification errors represent spectral signatures of pixels with mixtures of cover types. The pixel is labeled as change only when the location of a pixel in the red-NIR space migrated from a "core area" at time 1 to a different "core area" in time 2. Otherwise it is labeled as no change.

The 8km monthly composited AVHRR Pathfinder data were used to train the decision tree to determine values associated with “core areas” and “mixed areas” with the following steps: 1) aggregate the UMD 1km land cover product (Hansen et al., 1999) into the 5 cover types; 2) randomly select 1000 pixels (after buffering the polygons of contiguous land cover types by 1 pixel to avoid mixed pixels) for the forest, non-forest vegetation and bare cover types; 3) extract the red and NIR reflectance values for the selected pixels of the three cover types and the reflectance values of water bodies and burn scars from the Landsat TM data; and 4) for each region and each month, generate a decision tree from the 1000 pixels for each of the five cover types to find the boundaries of the “core areas” and “mixed areas” (see Hansen et al., 1998).

3.3.3.2 LUTs for the red-NIR space change vector method

The red-NIR space change vector method uses the red and NIR reflectances in time 1 and time 2 and the change direction and magnitude to distinguish the different types of change. The LUTs have the following form:

$$Change\_Type(r_{Red}^{T1},\ r_{Red}^{T2},\ r_{NIR}^{T1},\ r_{NIR}^{T2},\ A,\ q\ ) \qquad (3.9)$$

where A and q were computed with equations (3.1) through (3.5) and r_{Red}^{T1}, r_{Red}^{T2}, r_{NIR}^{T1}, r_{NIR}^{T2} are the red and NIR reflectance values of the beginning and ending positions of the vector. To generate this set of LUTs, the 1km AVHRR data were used to determine the reflectance values for forest, non-forest, and bare ground. The values for water bodies and burn scars were obtained from Landsat TM images as described previously because these types are not identifiable in the AVHRR data. For each of the 5 cover types listed in Table 3.1, five hundred randomly selected pixels in the agreed areas of the UMD’s (Hansen et al., 1999) and EDC’s (Loveland et al., 1997) 1km land cover classification product were used to determine values for r_{Red}^{T1}, r_{Red}^{T2}, r_{NIR}^{T1}, r_{NIR}^{T2} for each month. For each possible type of change in Table 3.1, the corresponding values for change direction q and magnitude A were computed with equations (3.1) through (3.5) from the 500 pixels. Applying the decision tree approach to the data of r_{Red}^{T1}, r_{Red}^{T2}, r_{NIR}^{T1}, r_{NIR}^{T2} and A and q for each possible land cover change, the characteristic ranges of these variables were determined and entered into the LUTs (Huang et al., 1998). Examples of these LUTs are listed in Table 3.3 for the regions and months corresponding to the test data listed in Table 3.2.

3.3.3..3 LUTs for the modified-delta space thresholding method

To implement the modified-delta space thresholding method, two sets of LUTs are needed. One set, "cover type LUTs", are used to determine the cover type for time 1 from the red and NIR reflectances. Mean values of red and NIR reflectances for each month and region are used to modify the delta values in equations (3.6) and (3.7) to compensate for seasonal changes in reflectances. These LUTs are similar to the LUTs represented by equation (3.8) for the red-NIR space partitioning method, but the latter include only the "core areas" without the

Table 3.3. The Look-Up Tables used to detect the specific land cover changes in the test data sets listed in Table 3.2 with the Red-NIR space change vector method

Data set and change type	**Bolivia** (South Tropical Region, July) Forest to non-forest vegetation	**Egypt** (North Region, June) Bare to vegetation	**Washington, DC** (North Region, May) Forest to urban
Criteria for Change Type LUT	(1) $A > 3.0\%$ & $q > 318°$ & $r_{Red}^{T1} < 3.6\%$ & $r_{NIR}^{T1} > 12.6\%$ or (2) $A > 3.0\%$ & $210 < q \leq 318$ & $r_{Red}^{T1} < 3.6\%$ & $r_{NIR}^{T1} > 12.6\%$	(1) $A > 23.3\%$ or (2) $10.8\% < A < 23.3\%$ & $q > 106\%$ & $r_{Red}^{T1} < 24.6\%$.	(1) $q > 172°$ & $r_{Red}^{T1} < 6.9\%$ & $r_{NIR}^{T1} > 27.6\%$ or (2) $A > 12.3\%$ & $127 < q \leq 178$ & $r_{Red}^{T1} < 4.6\%$ & $r_{NIR}^{T1} > 27.6\%$

"mixed areas." The other set of LUTs, the "change type LUTs", are used to determine the type of land cover change from the values of direction q and magnitude A. These LUTs are computed from the modified-delta values (dr_{Red} and dr_{NIR}) substituting the Δr_{Red} and Δr_{NIR} in equations (3.1), (3.2), and (3.3).

The randomly selected pixels for forest, non-forest, and bare and the Landsat TM data for water bodies and burn scars, as described in section 5.2 for deriving LUTs for the red-NIR space change vector method, are also used to derive the

LUTs for the modified-delta space thresholding method. The "cover type" LUTs were determined with a simple classifier from the randomly selected pixels. The "change type" LUTs were determined with the same simple classifier using equations (6) and (7). Examples of the two types of LUTs are shown in Table 3.4 for the specific types of land cover changes in the regions and months corresponding to the test data sets in Table 3.2.

Table 3.4. The Look-Up Tables used to detect the specific land cover changes in the test data listed in Table 3.2 with the modified-Delta space thresholding method

Data set and change type	**Bolivia** (South Tropical Region, July) Forest to non-forest vegetation	**Egypt** (North Region, June) Bare to vegetation	**Washington, DC** (North Region, May) Forest to urban
Criteria for the Cover Type LUT	$0\% \leq r_{Red}^{T1} < 6\%$ & $10\% \leq r_{NIR}^{T1} < 100\%$ for Forest	$0\% \leq r_{Red}^{T1} < 6.0\%$ for Bare	$0\% \leq r_{Red}^{T1} < 10\%$ & $10\% \leq r_{NIR}^{T1} < 100\%$ for Forest
Criteria for the Change Type LUT	$2\% \leq A < 100\%$ & $0° \leq q < 150°$	$2\% \leq A < 100\%$ & $0° \leq q < 150°$	$7\% \leq A < 100\%$ & $0° \leq q < 175°$

3.3.3.4 LUTs of the coefficient of variation and linear feature methods

The LUTs for the texture and linear feature methods simply identify a threshold for the difference in texture or linear feature between time 1 and time 2. Above this threshold, a pixel would be labeled as change. Because the spatial resolution of the AVHRR data precludes a possibility of determining texture and linear features at 250m resolution, the only available data for deriving the threshold are simulated MODIS data derived from Landsat TM images. Landsat TM data for all months in all regions are not available. Consequently, the threshold values were based on empirical examination of the available Landsat TM data.

3.3.3.5 LUTs for integrating various change detection results

The five change detection methods produce five results of detected changes. These results may not agree on whether change has occurred. To integrate the results and create a final result for the 250m MODIS land cover change product, a LUT for integrating the results from the different algorithms is needed. Based on experiments with different combinations of the results from the five methods on the three test data sets in Table 3.2, the following rule was found to give an acceptable result: if at least any three of the five methods label a pixel as “change”, then the pixel is labeled as “change”. This “algorithm integration rule” is implemented with a LUT. This LUT can be updated for any other “algorithm integration rules”.

A simple “time integration rule” for the three month result states that if at least any one of the time intervals (one month, two months, or three months) labeled the pixel as “change”, then the pixel is labeled “change” in the three-month change detection product. These integration rules require further testing with additional test sites.

3.3.4 Validation of the change detection methods

We tested the five change detection methods, implemented with the LUTs, on three pairs of MODIS data simulated from Landsat TM images. The test data represent tropical deforestation near Santa Cruz, Bolivia (Figure 3.7), agricultural expansion into desert areas around Alexandria, Egypt (Figure 3.8), and conversion of temperate mixed woodland to residential and commercial uses (Figure 3.9). The five algorithms were run on each of these test data sets. The result from the “algorithm integration rule” applied to the five change detection results and an integration result was obtained for each of these data sets. The results from each of the five methods and the integration were then compared with the validation data generated from bitmaps of known changed pixels as described in section 4.3 to test the performance of these methods. It should be noted that, because the change bitmaps were generated by visual inspection, false errors can result due to errors in the change bitmaps themselves.

Errors in the test results can be either of two types, commission errors where pixels that are not labeled as change by the change bitmap are falsely labeled as change, or omission errors where pixels labeled as change in change bitmaps are not labeled as change by the algorithm. These measures used to evaluate the performance of the algorithms are:

$$Commission\_Error[\%] = \frac{N_{commit}}{N_{predict}} \tag{3.10}$$

$$Omission\_Error[\%] = \frac{N_{omit}}{N_{bitmap}} \tag{3.11}$$

where N_{commit} is the number of pixels where the method labeled change but the actual change bitmap did not, $N_{predict}$ is the total number of pixels that the method labeled as change, N_{omit} is the number of pixels where the change bitmap labeled change but the method did not, N_{bitmap} is the total number of the change pixels in the change bitmap. The rate of correctly detected change pixles is the compensation of the omission error rate, that is, (100% - omission error).

The performance statistics of each of the five change detection methods and the integration of them are listed in Tables 3.5, 3.6, and 3.7 for the three test data sets, respectively. The spatial distributions of the commission and omission errors of these change detection results for the three data sets are demonstrated in Figures 3.10, 3.11 and 3.12. Commission errors were smaller than the omission errors. There were trade-offs between the commission and omission errors during the selection of the criteria for growing the decision trees of the change detection methods. The criteria were chosen in favor of smaller commission errors which would make the change detection product more conservative.

Figures 3.10, 3.11, and 3.12 show that the pixels incorrectly identified as no change are in close proximity to pixels correctly identified as change. Because the intent of the product is to flag areas undergoing change for further analysis with high resolution data rather than to identify change at each 250m pixel, we calculate the omission error for a 3 by 3 pixel moving window in addition to the error on a per pixel basis. For this calcualtion, if a pixel is labeled as change in the bitmap and any pixel in the 3 by 3 window around the bitmap pixel is identified as change from the algorithm, we consider the result to be correct. By this criteria, omission errors for the integrated results were 6.6 percent, 23.9 percent and 10.4 percent for the Bolivia, Egypt, and D.C. scenes respectively . The omission errors computed on the 3 by 3 window basis are listed in Column 4 of Table 3.5, 3.6 and 3.7.

The commission errors can also be computed on the 3 by 3 window basis. For this calculation, if a pixel is labeled as change by an algorithm and any pixel in the 3 by 3 window around the pixel was not labeled as change by the change bitmap, then we consider the labeling is a commission error. If there is one or more pixels labeled as change by the change bitmap around the pixeled label as change by an algorithm, then we consider the labeling by the algorithm to be correct. Based on this 3 by 3 window calculation, the commission errors (listed in the last columns of Table 3.5, 3.6 and 3.7) are all less than 10 percent.

For the Bolivia and Egypt data sets, the three spectral methods gave commission errors around or less than 10 percent while omission errors could go as low as 20 percent (e.g., the modified-delta space thresholding method) on a per pixel basis and 1 percent when considering the error in a 3 by 3 window. The Red-NIR space partitioning method gave the smallest commission errors (around or less than 10 percent) for all the three data sets compared with other methods. However, the omission errors for the Red-NIR space method were relatively high (from 30 percent to 90 percent on a per pixel basis and from 6 percent to 63 percent on the 3 by 3 window basis) compared to the other two spectral methods.

The CV change detection method labels a pixel as changed when its CV at time 1 is significantly larger or smaller than its CV at time 2. This occurred prevailingly in the Bolivia data set, where the land cover changed mainly from deciduous forest with higher level heterogeneity to more homogeneous crop lands, and in the Egypt data set, where the homogeneous desert were converted to irrigated, small agricultural patches which have higher heterogeneity. Consequently, the method worked relatively well for the Bolivia data set (35 percent commission error and 30 percent omission error) and the Egypt data set (40 percent commission error and 30 percent omission error). If the change bitmaps are buffered by one pixel around the edge to consider the effect of the 3 by 3 kernel used by the CV method, the commission error of the method can be reduced to 6 percent for the Bolivia data set and 25 percent for the Egypt data set. On the 3 by 3 window basis, the omission errors of the CV method are less than 5% for all three data sets.

The linear feature method identifies boundaries present at time 2 but not at time 1. In the Bolivia dataset, the vegetation covers are relatively homogeneous. Thus, the linear feature method had a relatively small commission error (20 percent) for the Bolivia data set compared with other data sets. The method misses the central pixels of changed areas, thus its omission errors are high for all the three data sets on per pixel basis (45 - 75 percent). However, if we compute the omission errors on the 3 by 3 window basis, the 7 to 24% omission rates are acceptable.

The Washington DC data set is different from the other two in terms of heterogeneity of the land cover (see the time 1 and time 2 images in Fig. 9). In this temperate urban area, the land cover is characterized with many small patches: small agricultural fields with different crop types, various kinds of roads and highways, commercial build-ups, residential areas, power line right-of-ways, etc. The changed areas marked by the change bitmap are also small patches. Because many pixels may consist of different cover types, the spectral difference between its time 1 and time 2 values may not be significant compared with the signal noises retained in the data. Therefore, the commission and omission error rates of all the five methods are large on per pixel basis (30 - 90 percent) except the red-NIR space partitioning method had a 11 percent commission error. The small patches especially damage the performance of the texture change detection methods (the CV and linear feature methods) which detect changes based on the emerging of border lines. The commission errors of these texture methods are larger than 80 percent for this data set. However, all of the five methods correctly identified the major changed areas (see the green areas in Fig. 12). The spatial patterns of the detected change areas by the three spectral methods and of the actual change bitmap matched reasonably well. Thus, on the 3 by 3 window basis, the omission errors for all the methods are reasonable (see the last column of Table 3.7).

The commission and omission errors of the integrated change detection results from the five methods are reasonable for the Bolivia and Egypt data sets (commission errors at 3 and 5 percent and omission errors at 49 and 28 percent respectively). For the Washington DC data set, the omission error of the integrated result is 69 percent which is higher than the omission errors of three of the five change detection methods. This indicates that the different methods missed different change pixels, in other words, different methods identified different pixels as change. This is the rationale for using multiple methods to gain confidence in the change detection results.

Table 3.5. Commission and omission errors of the five change detection methods and the integration of them tested against the Bolivia data set (The size of the data set is 308×342 pixels and change bitmap has 14822 actual change pixels).

Method	Commission Error (per pixel) [%]	Omission Error (per pixel) [%]	Commission Error (3x3 window) [%]	Omission Error (3x3 window) [%]
Red-NIR Space Partitioning	1.1	67.8	0.1	21.3
Red-NIR Space Change Vector	7.7	42.6	0.7	4.2
Modified-Delta Space Thresholding	8.4	17.1	0.8	0.7
CV Texture Change Detection	34.7	29.8	1.7	4.4
Linear Feature Change Detection	19.6	74.0	0.3	24.1
The Integration of the Five Methods	3.0	49.0	0.2	10.4

Table 3.6. Commission and omission errors of the five change detection methods and the integration of them tested against the Egypt data set (The size of the data set is 137×160 pixels and change bitmap has 5977 actual change pixels).

Method	Commission Error (per pixel) [%]	Omission Error (per pixel) [%]	Commission Error (3x3 window) [%]	Omission Error (3x3 window) [%]
Red-NIR Space Partitioning	0.8	29.3	0.0	6.6
Red-NIR Space Change Vector	10.6	34.9	0.3	1.8
Modified-Delta Space Thresholding	8.0	20.5	0.2	2.1
CV Texture Change Detection	39.8	29.8	8.3	0.5
Linear Feature Change Detection	31.8	45.0	2.7	7.4
The Integration of the Five Methods	5.2	28.4	0.1	6.6

Table 3.7. Commission and omission errors of the five change detection methods and the integration of them tested against the Washington, DC data set (The size of the data set is 342×297 pixels and change bitmap has 4331 actual change pixels).

Method	Commission Error (per pixel) [%]	Omission Error (per pixel) [%]	Commission Error (3x3 window) [%]	Omission Error (3x3 window) [%]
Red-NIR Space Partitioning	11.2	90.8	0.0	62.5
Red-NIR Space Change Vector	41.4	54.4	1.2	7.1
Modified-Delta Space Thresholding	32.2	59.4	0.7	13.7
CV Texture Change Detection	80.6	41.1	7.3	2.1
Linear Feature Change Detection	84.5	75.0	4.9	12.6
The Integration of the Five Methods	26.8	69.2	0.3	23.9

3.4 Constraints, Limitations and Assumptions

The at-launch version of the 250m MODIS land cover change product is based on an approach using multiple change detection methods to build confidence in the result. The methods are implemented with look up tables whose values are currently determined with reflectance values from the AVHRR Pathfinder data sets and Landsat TM images. The results of the test for a limited number of sites show the ability of the methods to identify change. We expect the methods to become more reliable when data for training the LUTs can be derived from more advanced sensors such as the Sea-viewing Wide Field-of-view Sensor (SeaWifs) and the future National Polar-orbiting Operational Environmental Satellite System (NPOESS), and especially real MODIS data available after launch.

There are several possibilities for improving the change detection algorithms described in this document as well as for improving evaluation of results. First, the algorithms are based on comparisons between only two dates. Incorporation of multi-temporal information would likely improve performance because there are times of year when different cover types display similar reflectances. For example, dense crops in the growing season can appear as green as forest or deciduous vegetation in the winter can appear as bright as bare ground. Because of these limitations, the at-launch version of the product will serve as only an alarm system. To create a comprehensive global land cover change monitoring system based on MODIS, more experience and knowledge of global scale change detection and real MODIS data are needed.

To build more confidence in each of the five methods and their different integration approaches, more test data sets are required. Although the three test data sets used in this document represents different landscapes in different geographic areas, we are processing test data sets for boreal forest changes, urbanization in rapidly developing countries, flooding and flood retreat, forest burning, irrigation agricultural development and deforestation in different areas. Especially, the methods were designed to label different type of changes simutaneously with the LUTs. Test data sets in which different types of land cover changes occurred within the same scene will be used to evaluate the capabilities of the methods in detecting these different types of change. In addition, more test data are needed to test the redundancy of the methods and to study the feasibility for combining the three spectral methods into one integrated, more robust spectral change detection method.

The compensation for seasonal changes in vegetation were included in the LUTs for the five change detection methods. The time 1 and time 2 for the three test data sets used in this document are the same month in different years and thus do not depict seasonal changes. Data sets with both real land cover changes and seasonal changes are needed to test the capabilities of these methods in distiguishing them.

The performances of the texture change detection methods are not satisfactory as shown in the above section. One inherent reason may be that we were using globally-uniform thresholds for labeling changes with the texture measures (CV or edges). The thresholds identified real change from texture in the Bolivia data set, but they identified false change in the Washington DC area (see Fig. 12) and the mountain areas in the north of the Egypt data (see Fig. 11). If larger thresholds were used, the commission errors for the Washington DC and Egypt data sets can be reduced, but the real borders in the Bolivia data set would be missed. This indicates that we need more area specific thresholds, rather than the single one, for the texture change detection methods. A full set of Look-Up Tables of the thresholds for the global texture change detection should be obtained from more remote sensing data available in the near future.

Another test for the performance of the change detection methods is the effects of misregistration of the time 1 and time 2 images. The geolocation accuracies for the MODIS 250m bands are designed to 20 percent of a pixel, i.e., 50m. If this level of geolocation accuracy can be actually achieved, then the maximum georegistration error between the time 1 and time 2 images will be 100m. A preliminary simulation study on misregistration effects shows that error due to misregistration is within the noise due to a combination of atmospheric and bidirectional effects. Further testing for the effects of the misregistration needs to be conducted using the test data with simulated misregistration errors.

For the post-launch version of the MODIS land cover change product, in addition to the outputs of the metrics layers for users to judge changes, we will also directly output a “Change Probability” measure considering the the uncertainties associatated with the intensities of various types of land cover change. Once we have real MODIS data and more knowledge of global scale land cover change detection is obtained, the post-launch version of the product is expected to be more comprehensive and reliable.

4. The MODIS Vegetation Continuous Fields Product at 500m Resolution

4.1 Introduction

This document describes a simple method based on linear mixture modeling to derive the global vegetation continuous fields product based on the currently available satellite data, which served as a prototype of the MODIS global vegetation continuous fields product. The computer code for using the MODIS data to create the MODIS global vegetation continuous fields product has been developed based on the methodology and experience of this prototype product. Once the MODIS data will be available, the computer code will be able to generate automatically the global vegetation continuous fields.

4.2 Overview and Technical Background

4.2.1 Satellite data for subpixel characterization of vegetation

Vegetation mosaics occur at all spatial scales on the earth's land surface. At the landscape scale, patches of trees, grass, and bare ground are distributed heterogeneously across most of the land surface. At the local scale, mixtures exist even within plots of several square meters. Boundaries between vegetation types can be fairly abrupt in some locations, such as the boundary between a forest and an alpine meadow at a tree line. More often, however, boundaries are not so abrupt and gradients in vegetation occur gradually across the landscape.

Accurate information on the global distribution of vegetation characteristics is fundamental to many aspects of earth systems science and global change, including models of water, energy, and trace gas exchanges between the biosphere and atmosphere, conservation efforts to maintain biodiversity, and other types of resource management [*Townshend et al.*, 1994]. The existing paradigm to describe the global distribution of vegetation categorizes the land surface into a discrete number of vegetation types [*DeFries et al.,* 1998; *DeFries and Townshend,* 1994; *Loveland and Belward,* 1997; *Matthews,* 1983; *Olson et al.,* 1983]. Consequently, vegetation is unrealistically represented in global climate and biogeochemical models by a small number of cover types with abrupt boundaries between them.

The approach to map vegetation according to a predefined classification scheme has several disadvantages [*DeFries et al.,* 1995b]:

1) Because each cell is categorized as one of a number of vegetation types, the approach does not fully utilize the information content of remotely sensed data to describe gradients and mosaics in the landscape.

2) Variation in the vegetation's characteristics within a defined vegetation type is obscured. Parameters generated in models utilizing the maps are therefore homogeneous in areas where heterogeneity in vegetation characteristics exists in reality. The loss of information that results when using discrete cover types to extrapolate land surface parameters is illustrated by reconstruction of albedo, leaf area index, and biomass from varying the number of land cover types, where differences among estimates are as high as 50 percent of the mean [*DeFries et al.*, 1995b].

3) Inevitable semantic differences among classification schemes create difficulties when comparing vegetation maps based on different schemes.

The disadvantages with traditional classification schemes provide the impetus for developing alternative approaches to more realistically describe the land surface as continuous rather than discrete variables [*DeFries et al.*, 1996; *DeFries et al.*, 1995b].

Several approaches are described in the literature to characterize vegetation at the subpixel level using remotely sensed data. Such approaches include: 1) fuzzy membership functions to estimate subpixel forest cover [*Foody*, 1994; *Foody and Cox*, 1994], 2) isolines in red and near-infrared scatterplots to estimate subpixel fractional canopy density, using geometric models of plant cover to infer the densities associated with the isolines [*Jasinski*, 1996], 3) empirical relationships between percent cover derived from high resolution data and attributes of coarser resolution data, using the relationships to extrapolate proportional forest cover over larger areas [*DeFries et al.*, 1997; *Iverson et al.*, 1989; *Iverson et al.*, 1994; *Zhu and Evans*, 1992; *Zhu and Evans*, 1994], 4) calibration of areal estimates from spatial aggregation of classifications derived from coarse resolution data taking into account the spatial arrangement of land covers at fine resolution [*Mayaux and Lambin*, 1997], and 5) linear mixture modeling to deconvolve proportional cover based on reflectances of "endmembers", or pixels containing 100 percent of the vegetation types of interest [*Adams et al.*, 1995; *Bierwirth*, 1990; *Pech et al.*, 1986; *Quarmby et al.*, 1992; *Settle and Drake*, 1993].

In this document , we use linear mixture modeling to derive global continuous fields of vegetation characteristics because it can be applied over large areas and because it is relatively simple. The linear mixture model is based on the assumption that the reflectance is the sum of the reflectances of each component within the pixel weighted by the respective proportional covers. It is based on the relationship:

$$R_i = \sum_{j=1}^{Q} r_{ij} x_j + e_i \qquad (4.1)$$

where R_i is the reflectance in band I, r_{ij} is the reflectance of component j in band I, x_j is the fractional cover of component j, e_i is the error term, and Q is the number of components. Furthermore, the model is based on the constraint that:

$$\sum_{j=1}^{Q} x_j = 1 \qquad (4.2)$$

Bosdiagianni et al [1997b] propose to augment the model to include higher order moments that describe the distribution of the endmember values about the mean. A method that allows the types and number of endmembers to vary on a per pixel basis, called multiple endmember spectral mixture analysis, has also been applied [*Roberts et al.*, 1998].

4.2.2 Requirements for global land cover in global change models

Biosphere-atmosphere models currently use land cover classification maps as a boundary condition to estimate a number of parameters, including fraction of photosynthetically active radiation (FPAR), leaf area index (LAI), and surface roughness. However, the vegetation characteristics that control exchanges of water, energy, and trace gases between the biosphere and atmosphere are relatively few [*DeFries et al.*, 1995b; *Running et al.*, 1994b; *Running et al.*, 1995]. DeFries et al. [1995b] conclude that the most important vegetation characteristics in controlling fluxes of water, energy, and carbon dioxide are : 1) growth form (tree, shrub, herb), 2) seasonality of woody vegetation (deciduous, evergreen), 3) leaf type (broadleaf, needleleaf), 4) photosynthetic pathway (C_3, C_4), 5) longevity (annual, perennial), and 6) type and intensity of disturbance (e.g., cultivation, fire history). Running et al [1994b; 1995] conclude that only the most fundamental characteristics of life form, leaf longevity, and leaf type are required. Thus, continuous fields of these vegetation characteristics would satisfy the modeling requirements as well as permit a more realistic depiction of the vegetation over the earth's surface.

Many of these required vegetation characteristics are observable with remotely sensed data, such as growth form, leaf type, and leaf longevity. Others, such as the distribution of C_3 and C_4 plants and intensity of disturbance are more difficult to detect. In this document , we concentrate on the subset of these characteristics that are amenable to remote sensing as a first effort to derive continuous fields at a global scale.

Biosphere-atmosphere models have generally been designed to use thematic land cover classifications rather than continuous fields as boundary conditions [*Dickinson,* 1995; *Henderson-Sellers et al.,* 1993; *Sellers et al.,* 1997; *Sellers et al.,* 1996]. Although some efforts have been made to capture spatial heterogeneity in vegetation by using mosaics of vegetation types and statistical measures [*Avissar,* 1992; *Bonan et al.,* 1993; *Dickinson et al.,* 1993; *Thomas and Henderson-Sellers,* 1991; *Wood et al.,* 1992], the use of continuous fields requires modifications in the models for deriving parameters from vegetation characteristics. For example, within the SiB2 model, FPAR is calculated from the Normalized Difference Vegetation Index (a ratio of red to near infrared reflectances that is correlated with the amount of photosynthetic activity). Relationships between NDVI and FPAR vary according to vegetation type [*Sellers et al.,* 1996]. With appropriate modifications to the model, proportions of woody and herbaceous vegetation from the continuous fields could be used to calculate FPAR from NDVI more realistically to avoid discrete boundaries between vegetation types and to allow for variations in FPAR within vegetation types.

4.2.3 Overview of This Section

This section of the document proposes continuous fields as an alternative paradigm from traditional classification schemes for describing global vegetation distributions. The continuous fields are a series of data layers, each of which provides an estimate of proportional areal coverage within the cell displaying the respective vegetation characteristic. For example, continuous fields describe the areal proportion of woody vegetation, herbaceous vegetation, and bare ground for each cell.

We describe a simple technique as an initial attempt to obtain continuous fields for three vegetation characteristics observable with remotely sensed data: growth form, leaf type, and leaf longevity. The fields are derived from the global 1 km resolution data set from the Advanced Very High Resolution Radiometer [*Eidenshink and Faudeen,* 1994], serving as a prototype for continuous fields to be generated from data collected by MODIS that will be launched on board the EOS AM1 platform in July, 1999. MODIS will provide data with improved spatial resolution (250 m to 1 km depending on the spectral band), spectral resolution, and atmospheric correction [*Running et al.*, 1994a].

The technique for deriving continuous fields is based on vegetation phenology measured by a number of multitemporal metrics. Training data derived from high resolution imagery for use in classification algorithms [*DeFries et al.*, 1998] are used to identify pure, endmember pixels in a linear mixture model. We then use the model to estimate aerial proportions of 1) woodiness (proportion woody vegetation, herbaceous vegetation, or bare ground), 2) leaf type (proportion of woody vegetation that is needleleaf or broadleaf) and 3) leaf longevity (proportion of woody vegetation that is evergreen or deciduous).

4.3 Algorithm of The Prototype Product of Global Vegetation Continuous Fields

4.3.1 Data

4.3.1.1 AVHRR data

We use data from the Advanced Very High Resolution Radiometer (AVHRR) on board the NOAA operational meteorological satellites in this study, in particular the 1km AVHRR data set processed under the guidance of the International Geosphere Biosphere Program [*Eidenshink and Faudeen*, 1994; *Townshend et al.*, 1994]. This data set includes daily and 10-day composites of 12 data layers at a spatial resolution of 1 km in the Goode's Interrupted Homolosine equal area projection. We extracted 10-day composites of the following layers: NDVI ((channel 2 - channel 1)/(channel 2 + channel 1)), channel 1 (visible reflectance, 0.58-0.68 microns), channel 2 (near infrared reflectance, 0.725-1.1 microns), channel 3 (thermal infrared, 3.55-3.93 microns), channel 4 (thermal, 10.3-11.3 microns), and channel 5 (thermal, 11.5-12.5 microns). Initially the data were collected continuously for 18 consecutive months beginning April 1, 1992, continuing through September 30, 1993. The period was subsequently extended to September 30, 1996. For this study, we use data from the twelve month period from April 1, 1992 to March 31, 1993. This avoids the period with the most marked orbital drift and hence reduces problems arising from very high solar zenith angles.

To reduce the possibilities of cloud contamination as well as to ease the problems of handling large volumes of data, we recomposited the 10-day composited images to monthly values based on the maximum NDVI value in the month [*Holben*, 1986]. Despite this procedure, noise in the data still persisted in some places. We applied a procedure to eliminate this noise by identifying spikes defined as those pixels 7 standard deviations away from the mean value from the remaining months as described in DeFries et al. [1998]. Monthly data associated with these spikes were flagged and excluded from subsequent processing. In addition, some locations clearly contained data from misplaced swaths. These pixels were also excluded from further processing.

From the monthly data, we then generated a number of metrics that characterize the annual phenological cycle of vegetation. These metrics were identified in previous research as those that maximize discrimination among vegetation types [*DeFries et al.,* 1995a; *DeFries et al.*, 1998]. The 24 metrics generated were the annual maximum, minimum, mean, and amplitude (difference between maximum and minimum) for the annual time series of NDVI in each of the 5 channels. To reduce the effect of noisy data from residual cloud cover, snow, streaks, scan lines, and remaining misplaced swaths, we chose to use only those 8 months of data with the highest NDVI values to generate the metrics. The 8 months with the highest NDVI values were selected separately for each pixel so that noisy data could be excluded regardless of the month it occurred. Monthly data flagged as noise as described above were not considered. The selection of only 8 months also enabled us to calculate metrics for high latitude areas which were labeled as "missing" because the processing procedure excludes pixels with low solar zenith angle during winter [*Eidenshink and Faudeen*, 1994]. In addition to 24 metrics derived from the 8 months with highest NDVI values, we also used 6 metrics derived from the 4 months with highest surface temperature measured in AVHRR channel 4. These metrics were chosen to counteract the tendency to eliminate the dry season, particularly in lower latitudes, when using only 8 months with highest NDVI values. We observed that with the metrics based on the 8 months of highest NDVI, grasslands and wooded areas were not readily distinguishable, most likely because grasslands in some areas in the tropics tend to be as green as forested areas except during the dry season. The additional metrics were calculated as the mean of the 4 months with the highest channel 4 values for each of channels 1 through 5 and NDVI. This process produced 30 metrics in total for use in the linear discriminant analysis (section 3.1).

4.3.1.2 Training data

Training data are required to derive the linear discriminants (section 3.1) and to test the linear assumptions of the mixture model (section 3.2). Ideally, training data would be available for all ranges of percentage woody vegetation, herbaceous vegetation, and bare ground and percentages of each leaf type and leaf duration. Such information is not available, particularly with global coverage. Consequently, we used training data developed in previous research for the purpose of land cover classification derived from the AVHRR 8 km Pathfinder data set [*DeFries et al.,* 1998].

The method to derive the training data is described in detail in DeFries [1998]. Briefly, it involves analysis of 156 scenes acquired by the Landsat Multispectral Scanner (MSS). The scenes were reprojected to the same map projection as the AVHRR data, rectified using ground control points and 1:250,000 navigational maps, and coregistered with the AVHRR data. In consultation with local and regional maps, we delimited areas in each scene occupied by the relevant cover type. The 13 cover types used in the classification are defined according to approximate height of mature vegetation in upper canopy, ground surface covered by vegetation, seasonality, and leaf type in DeFries et al. [1998] and are listed in Table 4.1.

The procedure to derive training data from the global network of Landsat MSS scenes was as described in DeFries et al. [1998], except that training pixels were identified for this work from overlaying the Landsat scenes with the 1 km AVHRR data as opposed to the 8 km AVHRR data. Training pixels for the 1 km data were labeled as such if 100 percent of the Landsat pixels in the 1 km cell were identified as the respective cover type. This process generated 632,637 training pixels in the 1 km AVHRR data set.

In order to create a more manageable data set to carry out the analysis, we sampled every eighth pixel and line of the 1 km AVHRR data and the training data. In addition, some areas of the world were clearly not well represented in the training data, likely due to a fragmented landscape making it impossible to obtain a homogeneous 1 km pixel. To overcome this problem, we selected additional pixels based on browsing the Landsat archives georeferenced with the 1 km AVHRR data based on visible physical features. The training sample used for this work subsequently contained 29,101 pixels.

Table 4.1. Definitions of land cover types for training areas used in this work
(from DeFries et al. [1998])

Cover type	Approximate height of mature vegetation in upper canopy	Ground surface covered by vegetation	Seasonality	Leaf type
1 Evergreen Needleleaf Forests	> 5 m	> 60%	Almost all trees remain green all year. Canopy is never without green foliage	needleleaf
2 Evergreen Broadleaf Forests	> 5 m	> 60%	Almost all trees remain green all year. Canopy is never without green foliage	broadleaf
3 Deciduous Needleleaf Forests	> 5 m	> 60%	Trees shed their leaves simultaneously in response to dry or cold seasons	needleleaf
4 Deciduous Broadleaf Forests	> 5 m	> 60%	Trees shed their leaves simultaneously in response to dry or cold seasons	broadleaf
5 Mixed Forests	> 5 m	> 60%	Neither broadleaf or needleleaf forest types has <25% or >75% landscape coverage	consists of tree communities with interspersed mixtures or mosaics of needleleaf and broadleaf forest types
6 Woodlands	> 5 m	tree canopy cover >40% and <60%.	can be either evergreen or deciduous with woody or herbaceous understories	can be either needleleaf or broadleaf
7 Wooded Grasslands/ Shrublands	> 5 m	tree canopy cover >10% and <40%	can be either evergreen or deciduous with woody or herbaceous understories	can be either needleleaf or broadleaf
8 Closed Bushlands or Shrublands	Bushes and shrubs <5 m	Bush and shrub canopy coverage >40%. Tree canopy coverage <10%. Remaining cover is either bare or herbaceous.	Shrubs or bushes can be either evergreen or deciduous	Bushes can be either broadleaf or needleleaf
9 Open Shrublands	Shrubs <2 m	Shrub canopy coverage >10% and <40%. Remaining cover is either bare or annual herbaceous type.	Shrubs can be either evergreen or deciduous	NA
10 Grasses	NA	Continuous herbaceous cover and <10% tree cover	NA	NA
11 Croplands	NA	>80% of the landscape covered in crop-producing fields	NA	NA

12 Bare	NA	<10% vegetated cover during any time of year. Includes land with exposed soil, sand, rocks, snow, or ice.	NA	NA
13 Mosses and lichens	NA	Mosses and lichens covering >60% of land surface with <40% woody canopy cover, or mosses and lichens >10% cover with remaining cover bare	NA	NA

4.3.2 Methods

The aim of this work is to provide continuous fields for three types of vegetation characteristics: life form (woody vegetation, herbaceous vegetation, and bare ground); leaf type (needleleaf, broadleaf); and leaf duration (evergreen, deciduous). Consequently, each pixel in the data layer is associated with seven layers (Table 4.2). The values range from 0 to 100 estimating the proportion by area within the 1 km pixel occupied by vegetation with the characteristic. Thus, the sum of woody vegetation, herbaceous vegetation, and bare ground for each pixel must equal 100. The values of the needleleaf and broadleaf layers sum to the percentage of woody cover, as do the values of evergreen and deciduous layers.

Based on the definitions used for deriving the training areas (Table 4.1), the approximate height of mature vegetation in the upper canopy of woody vegetation is greater than 5 m. Thus, the continuous field describing the proportional cover of woody vegetation represents the area occupied by vegetation with this height. Areas identified as herbaceous display grass or other types of herbaceous vegetation at some time in the annual cycle. In semi arid regions, this could include areas with herbaceous vegetation for only a portion of the year. In this scheme, shrubs are problematic. Because the method relies partially on reflectances in channel 1 representing shadow from standing vegetation, shrubs are likely to be considered herbaceous if they are low to the ground and woody if they are taller. Future efforts will attempt to identify shrubs as a separate component.

The procedure for deriving continuous fields of woody vegetation, herbaceous vegetation, and bare ground is shown in Figure 4.1. The steps in the method are: 1) to use the 30 metrics and the training data to calculate linear discriminants for use as variables in the linear mixture model, 2) determine endmember values of the linear discriminants based on the training data, and 3) apply the linear discriminants and endmembers to a linear mixture model to derive the continuous fields. Subsequently, a similar procedure is carried out to derive continuous fields for leaf type and leaf duration.

Table 4.2. Global continuous fields derived in this study

CHARACTERISICS CONSIDERED	CONTINUOUS FIELDS
Growth Form	1) Proportion of area occupied by woody vegetation
	2) Proportion of area occupied by herbaceous vegetation
	3) Proportion of area occupied by bare ground
Leaf Type	4) Proportion of woody vegetation that is needleleaf
	5) Proportion of woody vegetation that is broadleaf
Leaf Duration	6) Proportion of woody vegetation that is evergreen
	7) Proportion of woody vegetation that is deciduous

4.3.2.1 Linear discriminants for input into linear mixture model

To apply the linear mixture model to determine proportional cover of woody vegetation, herbaceous vegetation, and bare ground, we are first faced with two problems: 1) what metrics or combinations of metrics to use in the model, i.e. what values should constitute R_1,...R_j in equation 1, and 2) how to determine endmembers values, i.e. what values should constitute r_{i1}, ... r_{iQ}. With regard to the first question, it is not practical to apply the linear mixture model (equation 1) simultaneously to all of the 30 metrics derived from the annual time series of AVHRR. There are difficulties in minimizing the error (e) with a large number of equations. Furthermore, we observe that for most of the metrics the herbaceous vegetation is along a continuum between woody vegetation and bare ground, making it mathematically impossible to find unique solutions for combinations of the three types.

To overcome this problem, we derive linear discriminants to combine the 30 metrics into a smaller number of variables to be used as R_i in the model. Linear discriminants are linear combinations of variables with a maximal ratio of the separation of class means to within-class variance [*Venables and Ripley*, 1994].

Weightings for each metric are derived to maximize this ratio, and linear discriminants are the linear combination of these weighted metrics. To derive the linear discriminants, training data are required from which the class means and within-class covariance matrices can be calculated. We use the training data described in section 4.3.1.2 for this purpose. For woody vegetation, the training data are those training pixels in the cover types that represent forest, i.e. all those training pixels for cover types 1 through 5 (Table 4.1). For herbaceous vegetation, we take training data from the grassland cover type (type 10) and for bare ground from type 12. The linear discriminants were derived using the statistical package Splus version3.4 [*Venables and Ripley*, 1994].

The distributions of values for woody vegetation, herbaceous vegetation, and bare ground for the two linear discriminants are shown in Figure 4.2a. Comparison with a similar plot for two of the 30 metrics (Figure 4.2b), mean annual NDVI and maximum annual channel 4, shows the ability of the linear discriminants to improve discrimination between the three types (lower standard deviations and less overlap) as well as to identify herbaceous as an endmember component rather than an interim value between woody vegetation and bare ground.

The linear mixture model assumes linear relationships between R_i (in this case the linear discriminants) and the proportional cover of each component (x_j). Before applying the linear mixture model, it is necessary to test this assumption. Because fractional cover data are not available, we use instead the training data described in section 4.3.1.2. Based on the definition of each cover type, we identify representative values for percent woody, percent herbaceous, and percent bare (Table 4.3). For instance, cover types 1 through 5 are defined as 60 to 100 percent woody cover, so we choose a representative value of 80. We then examine the relationship between percent woody, herbaceous and bare to determine if the linear assumption is valid (Figure 4.3). Based on these plots and the high R^2 values (at least .95 in all but one of the plots), the linear assumption does not appear to be violated.

In the plots in Figure 4.3, we separate the values for two regions, one region being low latitudes (South America, Africa, South and Southeast Asia, and Australia) and the other region being temperate and high latitudes (North America and Eurasia). This was done because grasslands were found to exhibit substantially different values in the two regions.

Table 4.3 Representative values of proportional cover of woody vegetation, herbaceous vegetation, and bare ground for cover types defined in DeFries et al. [1998]

Cover Type	% woody vegetation	% herbaceous vegetation	% bare ground
1 evergreen needleleaf forest	80	20	0
2 evergreen broadleaf forest	80	20	0
3 deciduous needleleaf forest	60	40	0
4 deciduous broadleaf forest (low latitude)	80	20	0
4 deciduous broadleaf forest (high latitude)	80	20	0
5 mixed forest	80	20	0
6 woodlands	50	50	0
7 wooded grasslands/shrublands	25	75	0
8 closed bushlands or shrublands	82.5*	82.5*	12.5
9 open shrublands	62.5*	62.5*	37.5
10 grasses	5	95	0
11 croplands	10	90	0
12 bare	5*	5*	95
13 mosses and lichens	20	80	0**

* Value given is sum of woody and herbaceous vegetation.
** could contain up to 5 percent bare ground

4.3.2.2 Identification of endmember values

Accurate estimation of endmember values, or pure pixels, is crucial to successful application of the linear mixture model. Several approaches have been used, including values obtained from field or laboratory measurements [*Adams et al.,* 1995], manual selection of endmembers based on principal component analyses [*Bateson and Curtiss,* 1996], and deconvolution of the mixture modeling equation to solve for the endmember values when the fractional cover is known [*Asner et al.,* 1997; *Oleson et al.,* 1995].

We chose our endmembers according to the plots in figure 4.3. By extrapolating the regression to 100 percent, we can calculate the endmember values for the two linear discriminants for woody vegetation, herbaceous vegetation, and bare ground. These values are then used in the linear mixture model for r_{ij}. We separately determine endmembers for each of the two regions.

4.3.2.3 Application of the linear mixture model

With three components and two linear discriminants, the mixture model becomes:

$$R_1 = r_{1w} x_w + r_{1h} x_b + r_{1b} x_b \tag{4.3}$$

$$R_2 = r_{2w} x_w + r_{2h} x_b + r_{2b} x_b \tag{4.4}$$

$$x_w + x_h + x_b = 1 \tag{4.5}$$

where R_1 and R_2 are the first and second linear discriminants; $r_{iw,}$, r_{ih}, and r_{ib} are endmember values for woody vegetation, herbaceous vegetation, and bare ground respectively; and x_w, x_h, and x_b are fractional cover for woody vegetation, herbaceous vegetation, and bare ground respectively.

We then solve this set of simultaneous equations using the endmember values to determine the proportion of woody vegetation, herbaceous vegetation, and bare ground for each 1 km pixel. As there are the same number of equations as unknowns, we solve for x_j directly as opposed to a least squares [*Shimabukuro and Smith*, 1991] or Houghs transform [*Bosdogianni et al.*, 1997a] method to minimize the error.

The mixture model is applicable for those pixels for which the value of the linear discriminants is between the endmember values for the three components. For those pixels outside this range, we assumed the pixels to be either mixtures of two components or one component only (Figure 4.4). If the value for the first linear discriminant was less than the endmember value for woody vegetation or greater than the endmember value for bare ground, we labeled the pixel as 100 percent woody or 100 percent bare respectively (equations 6 and 7). If the value for the second linear discriminant was less than the endmember value for herbaceous vegetation, we labeled it as 100 percent herbaceous (equation 8), so that:

$$\text{if } R_1 < r_{1w} \text{ then } x_w = 100 \tag{4.6}$$
$$\text{if } R_1 > r_{1b} \text{ then } x_b = 100 \tag{4.7}$$
$$\text{if } R_2 < r_{2h} \text{ then } x_h = 100 \tag{4.8}$$

Pixels falling between the endmember values but outside of the triangle formed by the three endmember values were labeled as mixtures of two components, determined as the linear distance between endmember values. The second linear discriminant was used in the case of woody-herbaceous mixtures and herbaceous-bare mixtures and the first linear discriminant was used in the case of woody-bare mixtures. For example, if the pixel fell into the W+H space in Figure 4.4, the proportions for woody and herbaceous vegetation were calculated as:

$$x_w = (R_2 - r_{2h})/(r_{2w} - r_{2h}) \text{ and } x_h = (r_{2w} - R_2)/(r_{2w} - r_{2h}) \quad (4.9)$$

Similarly, for pixels in the H+B space:

$$x_b = (R_2 - r_{2h})/(r_{2b} - r_{2h}) \text{ and } x_h = (r_{2b} - R_2)/(r_{2b} - r_{2h}) \quad (4.10)$$

For pixels in the W+B space:

$$x_b = (R_1 - r_{1w})/(r_{1b} - r_{1w}) \text{ and } x_w = (r_{1b} - R_1)/(r_{1b} - r_{1w}) \quad (4.11)$$

4.3.2.3 Method for deriving continuous fields for leaf type and leaf duration

We derive continuous fields of leaf type and leaf duration by the following method:

1) We stratify the earth into three regions: low latitudes, mid and high latitudes, and Siberia. Each region is simplistically assumed to have two types of woody vegetation: broadleaf evergreen and broadleaf deciduous in low latitudes, needleleaf evergreen and broadleaf deciduous in mid and high latitudes, and needleleaf evergreen and needleleaf deciduous in Siberia. Though other types of woody vegetation can be found, for example needleleaf evergreen can be found in South America, we do not consider them in the derivation of the continuous fields. These regions were stratified by using the metrics and the training data in a decision tree classifier [*DeFries et al.*, 1998].

2) For each region, we calculate linear discriminants to determine the weightings of the 30 metrics that maximizes the separation of the two types of woody vegetation.

3) We determine the mean value of the linear discriminants for each woody type in each region. The proportion of each woody type is then taken as the linear distance between the means.

Continuous fields of leaf type (needleleaf, broadleaf) and leaf duration (evergreen, deciduous) are then determined by multiplying the proportion of each type from 3) above by the percent woody determined from the linear mixture model.

4.3.3 Results

Figures 4.5, 4.6, and 4.7 show the resultant continuous fields for each of the seven layers listed in Table 4.2. We made only one modification to the results. In the Sahara desert, the continuous field for percent bare indicate the presence of more vegetation than would be expected in some locations, possibly due to dark soil or the presence of lichens. To overcome this problem, we assigned a value of 100 to the percent bare data layer for those pixels identified in the Sahara region as bare ground in the IGBP DISCover product [*Loveland and Belward,* 1997]. This modification affected 3.8 percent of the total land surface.

The continuous fields show close to 100 percent woody vegetation in those areas with extensive forest cover. These areas include the humid tropical forests of South America, Africa, and Asia, the eastern coast of North America, and to a lesser extent the boreal forests of North America and Eurasia. The results show high values for herbaceous vegetation in areas that are dominated by agricultural crops and grassland, such as central North America, the steppes of Eurasia, and large portions of the Indian subcontinent. Based on this visual inspection, the global distribution of vegetation characteristics generally corresponds to known distributions.

A key question is how to quantitatively validate the continuous fields in the absence of global or even regional data on proportional cover. This is a difficult problem because even with high resolution data, we would expect mixtures of vegetation types to be present within a pixel. It is therefore somewhat problematic even to use high resolution data as a means to validate the continuous fields.

One approach to validate the continuous fields is by comparison with other land cover classification results. Through the definitions for the cover types, such as in Table 4.1, we can compare the continuous fields for consistency in the geographic distributions. Using the IGBP DISCover product [*Loveland and Belward,* 1997] and the 8 km land cover classification from AVHRR Pathfinder data [*DeFries et al.,* 1998],we compared the extent of woody vegetation, herbaceous vegetation, and bare ground on a continental basis (Figure 4.8). Note that the herbaceous vegetation category includes cropland and wooded grassland because cropland can include purely herbaceous as well as up to 20 percent tree canopy cover (Table 4.1). The only marked discrepancy between the three data sets is for woody vegetation in North America and Eurasia where the continuous fields product estimates lower percent woody values than the other two. This is likely due to the heterogeneous nature of the landscape in boreal areas, with numerous small lakes interspersed with forest. The continuous fields consequently indicate lower canopy coverage than classification products which label these areas as forests.

In this process, it must be kept in mind that any of the three data sets, the continuous fields or the two classification results, may be inaccurate so this procedure only provides a general understanding of the results rather than a true validation exercise. The comparison does suggest that the continuous fields give results consistent with the other two data sets.

4.4 Conclusions

Continuous fields offer an alternative to the traditional classification approach for using remote sensing data to characterize global land cover. The continuous fields offer the user of land cover data richer information content and more flexibility in the number and definition of classes to be used in earth system models. Ideally, the full information content in the continuous fields would be used in models, though it is possible to construct land cover maps from the continuous fields according to the user's definitions.

The method described in this document is a first attempt to derive continuous fields at the global scale. It applies a linear mixture model using training data derived from high resolution data for calibration. This training data was derived for the purposes of land cover classification so it is less than ideal for the purpose of continuous fields. Further effort is required to obtain calibration and validation data for the mixture model from very high resolution data, on the order of meters where mixtures are less likely to occur, in a number of globally representative locations. The training data do suggest, however, that the linear assumption implicit in the linear mixture model is valid. They also suggest that the method to use linear discriminants as inputs to the linear mixture model yields reasonable results.

Data from MODIS, to be launched on board the EOSAM1 platform in June, 1998, will provide higher spatial and spectral resolutions than have been available from the AVHRR. These data, as well as improved calibration and validation data, will allow refinements to the simple method described in this document for deriving continuous fields of vegetation characteristics. More sophisticated methods, such as those accounting for multiple endmembers [*Roberts et al.*, 1998], potentially allow the derivation of global continuous fields that take into account a broader range of vegetation characteristics.

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6. Figure Captions

(The mostly large figure files and this MS Word98 are stored at an anonymous FTP site at **ftp://ftp.geog.umd.edu/pub/landcover/MODIS_ATBD.** Any problems can be addressed to xzhan@geog.umd.edu)

Figure 2.1. Two-class hierarchical tree used in generation of the University of Maryland 1km product.

Figure 2.2. Procedure flow diagram, with sources of uncertainty/errors mandating the need for an interpretative step to create final product.

Figure 2.3. Subsets for boreal Russia, temperate United States and tropical West Africa. On left, red is maximum annual NDVI, cyan is minimum annual red reflectance. All three have the same linear stretch applied to both bands. On right is classified map. 1=needleleaf evergreen forest, 2=broadleaf evergreen forest, 3=needleleaf deciduous forest, 4=broadleaf deciduous forest, 5=mixed forest, 6=woodland, 7=wooded grassland, 8=closed shrubland, 9=open shrubland, 10=grassland, 11=cropland, 12=bare ground, 14=urban and built-up. Bar scale equals 300 km.

Figure 2.4. Vegetated/non-vegetated tree. Only those nodes which account for 5% or more of the respective class totals are shown. Paths to lesser nodes are shown with ~. The text in the ellipses gives the metrics used for the split, with the left-hand side less than the value indicated and the right-hand side greater. Metrics beginning with t, such as tmeanch1 are metrics derived from the 4 warmest months. Other metrics, such as maxndvi, are derived from the 8 greenest months. For example, tmeanch1 stands for the mean channel 1 value of the 4 warmest months. Maxndvi stands for the maximum NDVI value of the 8 greenest months. Values for channels 1 and 2 are in percent reflectance. Values for channels 3, 4 and 5 are in degrees Kelvin.

Figure 2.5. a)vegetated/non-vegetated tree. Red = largest node for vegetated class, cyan = largest node for non-vegetated class. Black = lesser nodes in the tree.
b)tall/short vegetation tree. Red = largest node for tall vegetation, orange = second largest, yellow = third largest. Cyan = largest node for short vegetation. Black = lesser nodes in the tree. Grey = bare ground class from previous tree. c) Forest/woodland tree. Red = largest node for forest, orange = second largest, yellow = third largest. Cyan = largest node for woodland, green = second largest. Black = lesser nodes. Dark grey = bare ground class. Light grey = short vegetation from previous tree. Refer to Figures 4, 6 and 7 to view node paths.

Figure 2.6. Tall/short vegetation tree. Only those nodes which account for 5% or more of the respective class totals are shown. Paths to lesser nodes are shown with ~. The text in the ellipses gives the metrics used for the split, with the left-hand side less than the value indicated and the right-hand side greater. Metrics beginning with t, such as tmeanch5 are metrics derived from the 4 warmest months. Other metrics, such as minch1, are derived from the 8 greenest months. For example, tmeanch5 stands for the mean channel 5 value of the 4 warmest months. Minch1 stands for the minimum channel 1 value of the 8 greenest months. Values for channels 1 and 2 are in percent reflectance. Values for channels 3, 4 and 5 are in degrees Kelvin.

Figure 2.7. Forest/woodland tree. Only those nodes which account for 5% or more of the respective class totals are shown. Paths to lesser nodes are shown with ~. The text in the

ellipses gives the metrics used for the split, with the left-hand side less than the value indicated and the right-hand side greater. Metrics beginning with t, such as tmeanch3 are metrics derived from the 4 warmest months. Other metrics, such as meanch1, are derived from the 8 greenest months. For example, tmeanch3 stands for the mean channel 3 value of the 4 warmest months. Meanch1 stands for the mean channel 1 value of the 8 greenest months. Values for channels 1 and 2 are in percent reflectance. Values for channels 3, 4 and 5 are in degrees Kelvin.

Figure 2.8. Final classified product. 1=needleleaf evergreen forest, 2=broadleaf evergreen forest, 3=needleleaf deciduous forest, 4=broadleaf deciduous forest, 5=mixed forest, 6=woodland, 7=wooded grassland, 8=closed shrubland, 9=open shrubland, 10=grassland, 11=cropland, 12=bare ground, 14=urban and built-up.

Figure 2.9. Areal comparison of 1km and 8km University of Maryland data sets. 1=needleleaf evergreen forest, 2=broadleaf evergreen forest, 3=needleleaf deciduous forest, 4=broadleaf deciduous forest, 5=mixed forest, 6=woodland, 7=wooded grassland, 8=closed shrubland, 9=open shrubland, 10=grassland, 11=cropland, 12=bare ground, 14=urban and built-up.

Figure 2.10. Training accuracies of each class. Graphs show the percentage of training pixels for each class as portrayed in the final map product. Over 50% of the errors involve the intermediate mixed assemblage woodland and wooded grassland classes. Class codes are those in Figure 2.9.

Figure 2.11. a) UMd map for EPA region 3. b) EPA MRLC Region 3 map. c) UMd map for Germany. d) CORINE map for Germany. 1=needleleaf evergreen forest, 2=broadleaf evergreen forest, 3=needleleaf deciduous forest, 4=broadleaf deciduous forest, 5=mixed forest, 6=woodland, 7=wooded grassland, 8=closed shrubland, 9=open shrubland, 10=grassland, 11=cropland, 12=bare ground, 14=urban and built-up. Black areas are for classes which do not aggregate into the UMd scheme such as wetlands for the EPA map and vineyards for the CORINE map. Bar scale equals 300 km.

Figure 2.12. Areal comparisons of UMd map product and other regional land cover maps derived from high-resolution data. Class codes are those in Figure 2.9.

Figure 2.13. a) Comparison of UMd and NASA Pathfinder Humid Tropical Deforestation Project maps for Colombia, Peru and Bolivia. b) Comparison of UMd and NASA Pathfinder Humid Tropical Deforestation Project map for the Democratic Republic of the Congo. Bar scale equals 300 km.

Figure 2.14. Plot of FAO total forest cover country statistics versus predicted woody cover of UMd product in millions of square kilometers. a) UMd forest (>60% tree canopy cover) versus FAO forest. b) UMd forest plus woodland (>40% tree canopy cover) versus FAO forest. c) UMd forest plus woodland plus wooded grassland (>10% tree canopy cover) versus FAO forest. d) best agreeing of the three UMd canopy closure figures versus FAO forest.

Figure 2.15. Global area totals for aggregated classes of the IGBP DISCover and UMd 1km maps. Forest/woodland represents all forest classes plus the woody savanna class for the DISCover map and all forest classes plus the woodland class for the UMd map. Grass and shrubs represents both shrub classes, the grassland class and the savanna class for the DISCover map and both shrub classes, the grassland class and the wooded grassland class for the UMd map. Barren/ice is the combined barren class and permanent snow or ice class for the DISCover

map and the bare ground class for the UMd map. Crops, urban and wetlands represent individual classes from the respective maps.

Figure 2.16. Global agreement of tall versus short vegetation for the IGBP DISCover and UMd 1km maps. Tall vegetation represents all forest classes plus the woody savanna class for the DISCover map and all forest classes plus the woodland class for the UMd map. Short vegetation is all other classes combined.

Figure 2.17. Global area totals for individual classes of the IGBP DISCover and UMd 1km maps, with the IGBP name listed. The UMd woodlands class is plotted as woody savanna, the wooded grassland class is plotted as savanna and the bare ground class is plotted as barren.

Figure 2.18. Full resolution snapshots of areas depicting the general differences between the DISCover and UMd map products. The permanent wetlands and snow and ice classes are absent from these windows, leaving only the cropland/natural vegetation mosaic class as the only category not in common between the data sets. The DISCover product is on the left, and the UMd product is on the right with both representing 500 km by 500 km squares. a) an area in southwest Australia centered at 117d29'E, 33d04'S. b) an area along the Canada/United States border in the Pacific northwest centered at 118d10'W,48d16'N. c) an area in the south of France centered at 0d33'E,44d57'N.

Figure 3.1. Data processing flow chart for the at-launch version of the MODIS 250m global land cover change product.

Figure 3.2. The processing procedure for compositing the 32 daily observations of the Band 1 and Band 2 reflectance values for each pixel.

Figure 3.3. Time intervals over which land cover changes will be detected in the at-launch version of the MODIS 250m land cover change product.

Figure 3.4. The relationship between the Red-NIR space and the Brightness-Greenness space and the typical signatures of various land cover types.

Figure 3.5. Typical change vectors associated with no forest change, deforestation and forest burning processes in the Red-NIR space representing the Brightness-Greenness space.

Figure 3.6. Change vectors in the Delta spaces. The coordinates of change vector magnitude and direction are overlaid with the Delta spaces.

Figure 3.7. The MODIS 250m resolution images simulated from the Landsat TM band 3 and 4 reflectance data of the Santa Cruz, Bolivia area.

Figure 3.8. The MODIS 250m resolution images simulated from the Landsat TM band 3 and 4 reflectance data of the Alexandra, Egypt area.

Figure 3.9. The MODIS 250m resolution images simulated from the Landsat TM band 3 and 4 reflectance data of the Washington, DC area.